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Analyzing emotion regulation using multimodal data

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by

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Analyzing emotion regulation using multimodal data

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Abstract

An emotion is a state of one's mind that derives from situations, mood, etc. Understanding people's emotions is a complex problem. People express their emotions using facial expressions or via voice modulations; also, they use emotion regulation strategies such as cognitive reappraisal and expressive suppression in certain instances. Emotion regulation is a method by which we alter our emotions by changing how we express and perceive different situations. Understanding these emotional regulations helps to interact better, communicate and provide care. In this research, we analyze, visualize the differences and distinguish the emotions of disgust and humor with and without emotion regulation strategies. This is done by analyzing electrocardiography data (EKG), electroencephalogram data (EEG), galvanic skin response (GSR), and facial action units (FAU) data with machine learning algorithms such as convolutional neural networks (CNN), gated recurrent units (GRU), long short term memory (LSTM) and support vector machines

(SVM). The data is collected by exposing participants (N = 21) to an inductive emotion video in a controlled environment.

Acknowledgments

Firstly, I would like to express sincere gratitude to my advisor Dr. Ifeoma Nwogu for her support, patience, and unparalleled computer vision and machine learning expertise. Without her continuous encouragement, I would not have completed this thesis.

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Chapter 1

Introduction

1.1 Introduction

Emotions play a vital role in how we as humans behave, interact and react. They decide the actions that we take daily. Many times people hide their emotions. Emotion regulation is defined as an attempt to alter the emotional response. Most of the time, emotion regulation is an excellent technique to keep our emotions in check. But using emotional regulation to cheat or even hide the pain or sorrow can cause many problems. Understanding whether a person is freely expressing or suppressing, or reappraising their emotions help us to understand each other at a much higher level. For doctors, this understanding will aid in providing appropriate care. For interrogators understanding the emotion regulation technique the suspect is expressing will help make the right decisions regarding whether the person is hiding the truth or speaking the truth. The emotion regulation technique is hard to decipher using just facial expressions or voice. In such cases, physiological data such as Electrocardiography(EKG), Electroencephalogram(EEG), Galvanic skin response(GSR), Electromyogram(EMG) provide more significant insights in understanding emotion regulation, as these signals are direct responses to the emotions that we feel. Using these three physiological data modalities, along with facial expressions, we are classifying and comparing emotion regulation strategies: cognitive reappraisal, emotion suppression, and free expression for humor and disgust emotions.

1.2 Motivation

Dr. Gross(2002) conducted a study on the consequences of emotion regulation strategies(reappraisal and suppression). He collected finger pulse rate readings from participants while watching a disgust-inducing video and also developed a questionnaire to find the participant's differences in both regulation strategies. From the results, he concluded that reappraisal decreases emotion experience and behavioral expression and has no impact on memory, whereas suppression decreases behavioral expression but fails to reduce emotion experience and impairs memory [10]. We want to expand on this work by collecting different modalities of data. We are interested in classifying these emotion regulation strategies by analyzing the behavioral and emotional experiences of the participants using machine learning models such as Convolutional neural network(CNN), Gated recurrent unit(GRU), Long short term memory(LSTM), and Support vector machine(SVM).

1.3 Objectives

The objectives of this study are to

- Expand on the work previously done by Gross by comparing reappraisal and suppression methods of emotion regulation using multimodal channels[10].
- Investigate whether disgust and humor emotions can be classified using EEG and GSR signals.
- Develop computational models and visualization schemes to analyze the three emotion regulation strategies (free expression, suppression, and cognitive reappraisal) using different modalities (EEG, EKG, GSR, and facial videos).

1.4 Related Work

1.4.1 Physiological related work

The baseline for this study is taken from Gross's work in 1998[10]. Gross collected physiological data and observed the relation between reappraisal and suppression using the emotion of disgust. In 2008 Goldin et al. [9] analyzed reappraisal and suppression of negative emotion using 15 seconds of emotion-inducing videos. Functional magnetic resonance imaging (fMRI) was collected and drew comparisons between reappraisal and suppression of emotional regulation techniques, showing that reappraisal produced prefrontal cortex responses whereas suppression produced late prefrontal cortex responses. In 2012, Kim et al.[15] investigated cognitive reappraisal on men and women by inducing emotion using negative pictures similar to Goldin et al. [9]. They collected corrugator (EMG) and GSR data (physiological data). In this paper, the authors concluded that when participants reappraised for increased negative emotions, the corrugator and skin conductance values increase. When the negative emotion is decreased, it results in corrugator and skin conductance values in the participants dropping. Olatunji et al.[19] conducted a study with 95 participants to identify the difference between fear and disgust-based anxiety disorders. Participants were shown both fear and disgust emotion-inducing videos, and a comparison is made between reappraise and suppress strategies. The authors concluded that the respondents experienced significantly less emotional distress using reappraisal than suppression. Nwogu et al.[18] compared suppression with free expression to understand the different physical manifestations that happen using amusement emotion. The authors collected GSR and Facial Action Units(FAUs) and concluded that FAUs for amusement suppression are very different from amusement expression. Features associated with positive emotions were dominant during free expression, and features associated with sadness were dominant during suppression.

1.4.2 Technical related work

Convolutional neural networks

In the past, CNNs are used to distinguish emotions. Bansal et al. [7] used the facial expression, speech, and gestures of humans to detect emotions with 98.8% accuracy. In 2018 Wang et al[26] used 3D CNNs called EmotioNet to recognize emotion states. They used raw data from EEG to understand the spatial and temporal features and then classify the emotions. Deep CNNs are also used to classify the emotions using EEG when the subjects are listening to music[14]. Our approach is taking it a step further by using Deep CNN to identify and classify emotion regulation.

Recurrent neural networks

Because they retain critical information over time, recurrent neural networks(RNNs) are usually used to analyze time-series data. A lot of previous work was done to distinguish emotion using speech. Wollmer et al. [28] used an LSTM (a variant of RNN) to classify the valence(the extent to which an emotion is positive or negative) and activation of the emotion on the data that was recorded while humans interacted with a Sensitive Artificial Listener. Another variant of RNN is GRU which simplifies the LSTM. In research, GRUs are found to be outperforming other LSTM in terms of CPU time and also in parameters update and generalization[4]. This paper used GRUs and LSTMs to distinguish between emotion regulation strategies with GSR as input. GSR data that we collected is a continuous stream of information; our goal was to identify the GSR sequence patterns and classify the emotion regulation strategy.

Support vector machines

SVMs are widely used for pattern recognition in high dimension problems[25]. In this paper, we used a least-squares SVM to identify the emotion regulation using features obtained from GSR data.[24]. SVM is used in our study to identify the emotions of humor and disgust. We collected the data such as mean, standard deviation, etc., using GSR and would like to use an SVM to classify the emotions on a higher dimension.

Chapter 2

Background

In this chapter, an overview of the data (brain waves, GSR, and heart rate) and the algorithms used in this work are provided.

2.1 Physiological background

2.1.1 Brain waves

Electroencephalography is a process to record the electrical activity produced by the billions of neurons in the brain. The electrical activity is called brain waves. Neurons produce electrical signals to transmit information which reaches other neurons. EEG cap figure 2.1 has 32 sensors. EEG cap is placed on the head of the participant such that the sensors comes in contact with the scalp. Sensors capture the electrical signals and the software collects these signals and display them on the screen for us to look at in real time figure 2.2

Figure 2.1: EEG Cap

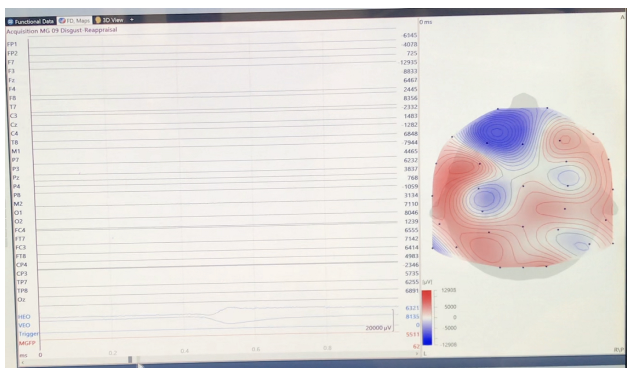

Figure 2.2: EEG sensor readings on curry software

2.1.2 Galvanic skin response

GSR is the measure of the electrical conductivity of our skin. Our body has 3 million sweat glands. The density of these sweat glands is high on our forehead, cheeks, palm, and soles of our feet. Emotion stimulation causes sweating on our palms and feet. Galvanic Skin Response originates from the autonomic activation of sweat glands in the skin. By changing the balance of positive and negative ions in the secreted fluid, electrical current flows more readily. The electrical current is the skin conductance, which is captured by placing sensors on the palm of a hand.[1]. GSR sensors and readings are shown in figure 2.3 below.

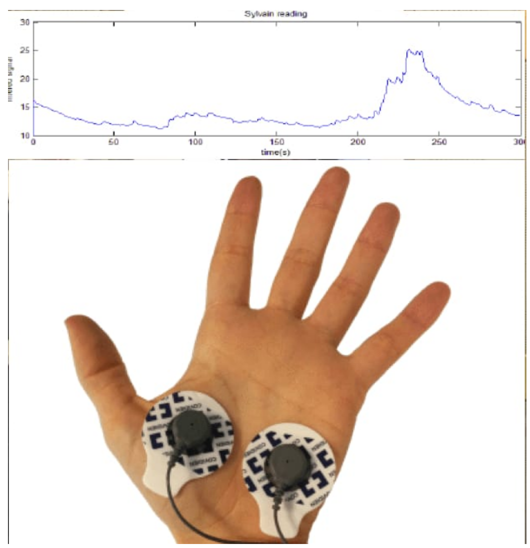

Figure 2.3: GSR signal readings and the sensors on the palm

2.1.3 Heart rate

Heart rate is directly correlated with the emotional state of a person. The autonomic nervous system controls physiological and emotional states according to the situation. The changes in these states are directly related to the varying heart rate. EKG is used to collect the heart rate.[2] Some researchers showed children videos of stressful contents while the GSR, heart rate, and facial expressions are measured. The researchers concluded that the children with higher heart rate change are more likely to feel sympathy and less likely to feel emotional distress[5].

2.1.4 Electromyography data

In the human body, various muscles act according to the nerve impulses from the brain. Using EMG, these electrical signals or impulses of various muscles are collected. Facial EMG is generally recorded bipolarly with small surface electrodes located close to each other. The EMG responses from the facial muscles express the emotions such as fear, disgust, happiness, joy.[12].

For this project, we reduced the scope to the collection of zygomaticus and corrugator supercilii as it is shown that the emotions of fear and disgust cause the impulses in these muscles. The locations where the EMG measures can be collected on the face are shown in the figure 2.4.

2.2 Technical background

2.2.1 Neural Network

Neural networks (NN) are algorithms that are loosely modeled based on the human brain. They came into existence around 1950s[13]. NNs are best known for modeling complex classification and regression tasks by adjusting

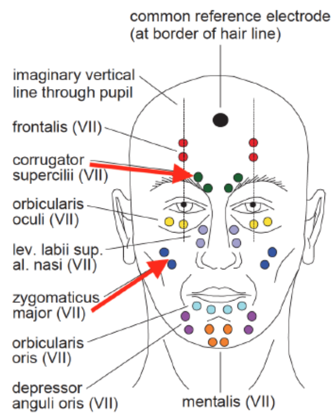

Figure 2.4: Exhaustive set of locations where EMG measures can be collected. The red arrows show the zygomaticus and corrugator supercilii used to collect the data in this project.[3]

the cost function to converge at a minimum using the pre-labeled data as input. A sample neural network is shown in the figure 2.5. Data is fed into the network as input in the form of features. All the inputs are multiplied with the weights and added together. A bias b is added to the summation. This sum is sent through an activation function. Let x_1, x_2 and x_3 are the input features, w_1, w_2, w_3 are the weights corresponding to the features, b is the bias and $h(x)$ (equation - 2.1) is the output.

$$h(x) = (\sum_{i=1}^{3} x_i * w_i) + b \tag{2.1}$$

A loss function is calculated using the actual label value to the calculated label value. The goal is to minimize the loss function by using back

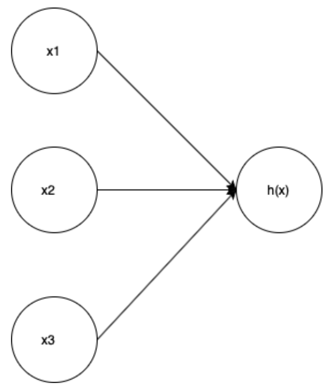

Figure 2.5: Neural Network

propagation[22], which is used to adjust the weights and bias, and thus learning happens.

2.2.2 Deep Neural Network

A deep neural network (DNN) is used when large datasets need to be trained. DNN has multiple hidden layers. A hidden layer has a weight parameter assigned to it. DNN takes input from the previous layer, calculates the dot product of inputs and weights, and adds bias. The result is passed on to the next layer.

Convolutional neural network

CNN(figure - 2.8) is a member of the family of DNN. CNN uses the spatial structure of data to model the data. CNN's are used mainly for image recognition and classification. Three different layers are used in CNN.

Convolutional layers

The convolutional layer(figure 2.6) has a kernel that will move across the image and learns features present in the images. The patterns learned are the feature maps. These feature maps are convoluted over the images, which results in a matrix called the activation map. A value close to one present in the activation maps suggests that the feature map found a similar feature in the input image. The operation that is performed in a convolution layer is element wise multiplication of the kernel and where the kernel is spatially present on the image. The value is determined by using the following formula.

Let the kernel size be m*m and the image size be n*n. g be the output value, h be the pixel value at a location in the input image, x be the value on the kernel [16]. The output g is defined in the equation 2.2.

$$g_{k,l} = \sum_{i=1}^{m} \sum_{j=1}^{m} x_{i,j} hk + i - 1l + j - 1 \tag{2.2}$$

Pooling layers

The pooling layer(figure 2.7) helps the features be invariant of the rotated, scaled, or even at a different position. There are two kinds of pooling, max pooling, and average pooling. In this paper, we will be using max-pooling only. Max pooling will consider all the pixels that fall under a kernel and

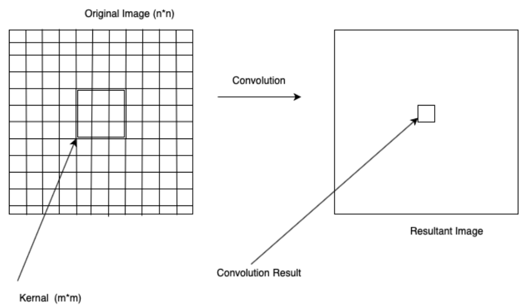

Figure 2.6: Convolution layer

calculates the maximum value

Let the kernel size be m*m, the image size be n*n, g be the output value (equation - 2.3) and h be the pixel value on the input image.

$$g_{k,l} = max\{x_{k+i-1,l+j-1} \forall 1 \leq i \leq m and 1 \leq j \leq m\} \tag{2.3}$$

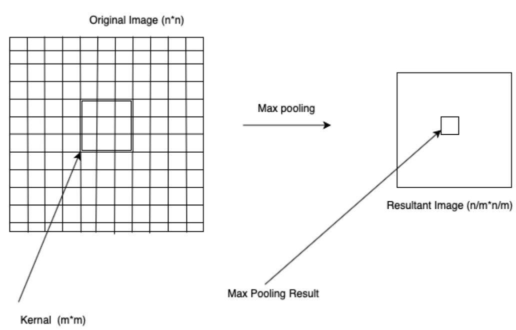

Figure 2.7: Max pooling layer

Rectified linear unit

Rectified linear unit (ReLU) is an activation function which is used to prevent the gradient from saturating. ReLU will help in faster convergence and training of data. Let n*n be the size of the image h be the input image and g be the output value (equation - 2.4)

$$g_{i,j} = max\{0, h_{i,j}\} \forall 1 \leq i \leq nand 1 \leq j \leq n \tag{2.4}$$

Fully connected layer

A fully connected layer has every node in the input layer connected to every node in the current layer. That means each output node is dependent on each input node. A fully connected layer will take all the inputs and combine them for the activation layer to process and classify an input.

Back-propagation is used to train the CNN. A cost function is calculated, which will penalize the weights when the images are wrongly classified concerning the ground truth, and the kernel learns the features of the images.

Some of the other hyperparameters which are adjusted are learning rate, batch normalization, and dropout. If the learning rate is low, the network will take longer to converge. If the learning rate is high, the network may miss the minimum. Batch normalization is used to increase the model's stability by normalizing the output of the previous activation layer. Batch normalization reduces overfitting, which helps in using a higher learning rate and faster convergence. Dropout also helps in reducing the problem of overfitting.[23]

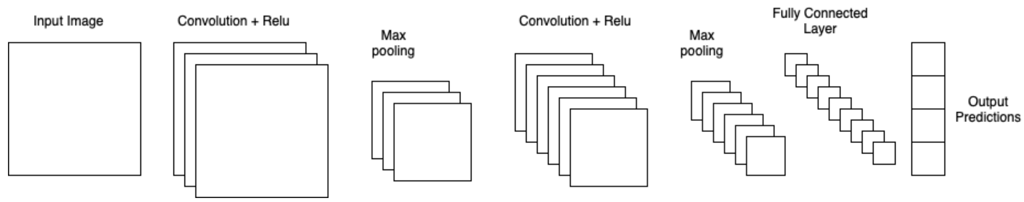

Figure 2.8: Convolutional Neural Network

Recurrent neural networks

An RNN is another variant of NN with a hidden state which is the previous period's output. In a NN, we treat all the inputs and outputs as independent, while in an RNN (figure - 2.9) the output depends on all the previous inputs that have been fed into the model. The hidden state learns patterns in the sequence of input and helps to identify the sequence.

Take a sequence $X = x_0, x_1, x_2, ...x_{t-1}$ as input. *t-1* is total number of time steps for the sequence. h_n is the hidden state at a time step n in time step range {*0, t-1*}. Hidden state is updated by the following equation 2.5 and 2.6.

$$h_n = \begin{cases} 0 & \text{when n = 0} \\ \text{g(h˙n-1 , x˙n)} & \text{when n != 0} \end{cases} \tag{2.5}$$

To update the hidden state

$$h_n = g(u * x_n + w * h(n-1)) \tag{2.6}$$

where u is the weight vector of hidden layer

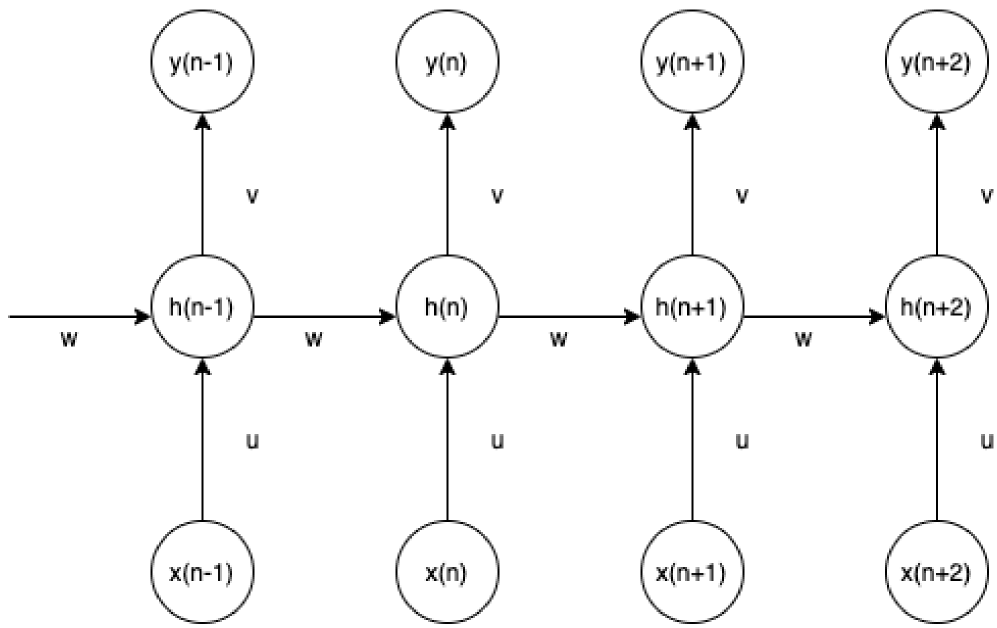

Figure 2.9: Recurrent Neural Network

v is the weight vector of output layer

w is the weight vector of the time steps

g() is the activation function which can be Tanh, relu or sigmoid to smooth the non linear equation.

The weights are trained using back-propagation through time[27]. RNN is really good at sequence classification, time series data prediction etc. RNN computes the output at an instance by processing all the inputs over time through a linear function. The major drawback for RNN is the vanishing gradient. Vanishing gradient happens over long period of time steps, the gradient diminish and does not have effect on the initial time steps which hinders the learning of weights. To combat vanishing gradient problem there are alternative RNNs such as GRU and LSTM.

Long short term memory

LSTM was first introduced by Gers et al[6]. LSTM are a variant of RNN, with one extra state called memory. Memory will help to retain the important information and does not let vanishing gradient happen which is a problem in RNN.

Let the input be x,

previous cell output *h(n-1)*, previous memory state *c(n-1)*,

U_c be the weight vector for memory gate,

U_I be the weight vector for input gate,

U_f be the weight vector for forget gate,

U_o be the weight vector for output gate with respect to input for the current time period n. Similarly weights vector W are the weights with respect to previous output *h(n-1)*.

In the figure 2.10 LSTM cell, there are three gates

1. Forget gate (f)

Forget gate (equation - 2.7) decides whether to withhold or empty the memory learnt from the previous time period.

$$f_n = \sigma(x_n * U_f + h_{n-1} * W_c) \tag{2.7}$$

2. Memory state (c)

Memory state (equation - 2.8) calculates which patterns are to be stored.

$$c_n = tanh(x_n * U_c + h_{n-1} * W_c) \tag{2.8}$$

3. Input gate (i)

Input gate (equation - 2.9) decides which values will be updated.

$$i_n = \sigma(x_n * U_i + h_{n-1} * W_i) \tag{2.9}$$

4. Output gate (o)

The output gate(equation - 2.10) calculates the output for the time step based from the previous time step output and the input of the current time step.

$$o_n = \sigma(x_n * U_o + h_{n-1} * W_o) \tag{2.10}$$

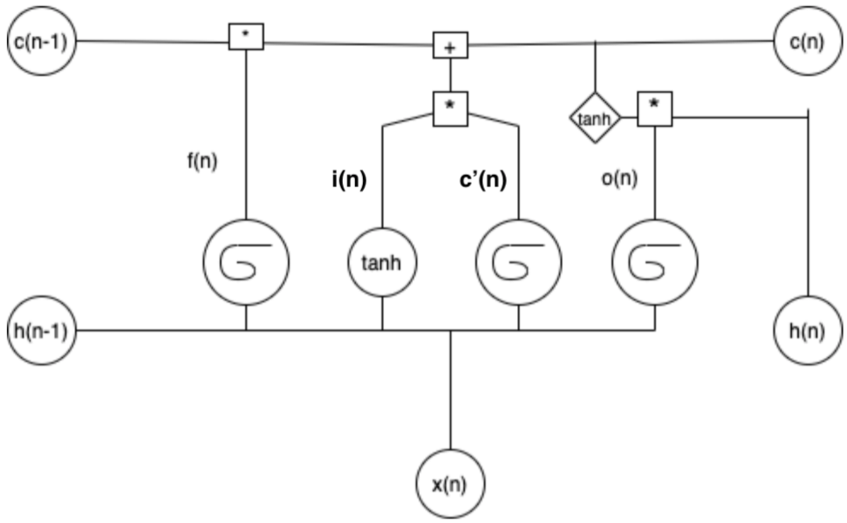

Figure 2.10: LSTM cell

Gated Recurrent Unit

GRU is another variant of RNN, which also has a memory to combat the vanishing gradient problem. GRU was first introduced by Cho et al.[4] It has two gates: update gate and reset gate decides which information is relevant and what is not. GRU cell(figure - 2.11) has two gates.

Let the input at an time step n be x_n, previous cell output be h_{n-1}.

1. Update gate (z)

Update gate (equation - 2.11) determines how much of the past information

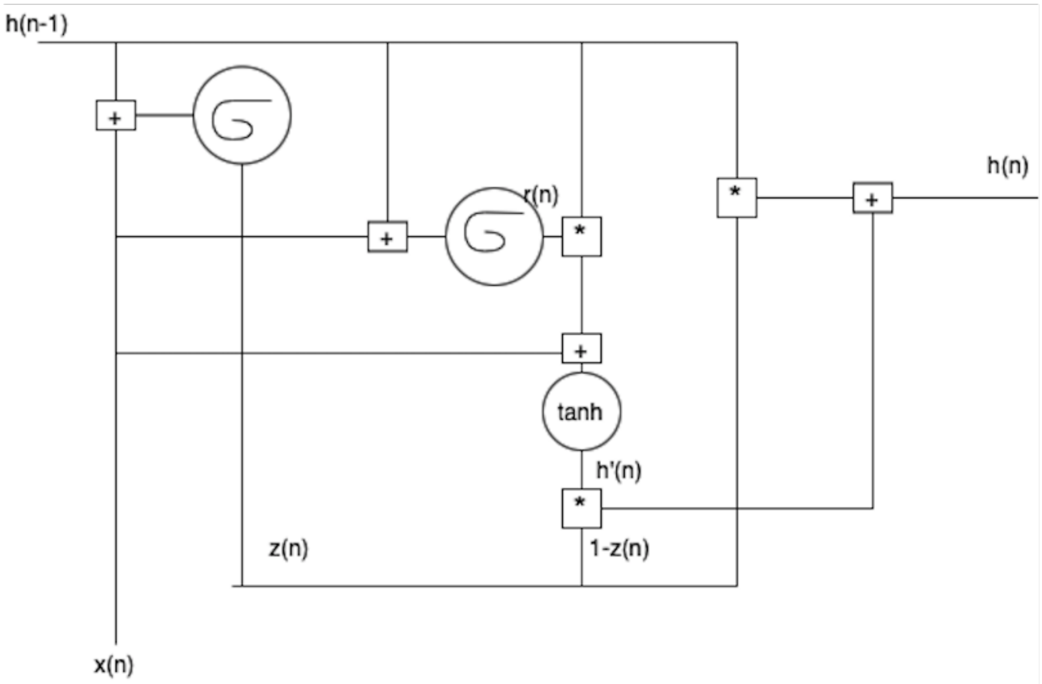

Figure 2.11: GRU cell

needs to be maintained and should be passed to the future.

$$z_n = \sigma(W_z x_n + U_z h_{n-1}) \tag{2.11}$$

2. Reset gate (r)

Reset gate (equation - 2.12) determines how much of the past information should be forgotten and is not useful.

$$r_n = \sigma(W_r x_n + U_z h_{n-1}) \tag{2.12}$$

3. Memory state (h')

Memory state(equation - 2.13) is the intermediate state before we calculate the final output state.

$$h'_n = tanh(W_h x_n + (r_n.h + n - 1)U_h \tag{2.13}$$

4. Output state (h) Output state(equation - 2.14) is the output of the current time period.

$$h_n = z_n h_{n-1} + (1 - z_n)h'_n \tag{2.14}$$

GRU has fewer operations than the LSTM, which results in faster results and less computational power required.

2.2.3 Support vector machine

SVM is a supervised machine learning algorithm that is used for classification and regression. The goal of SVM is to find the optimal hyperplane that can maximize the separation between the data points of different classes. Apart from linear classification, SVM utilizes kernel, which means it maps the inputs to a higher dimension space and performs non-linear classification.

Linear classification (figure - 2.12): Let the n training points are $(\vec{x_0}, y_0), (\vec{x_1}, y_1), ...(\vec{x_{n-1}}, y_{n-1})$. Where y_i is either 1 or -1. The aim is to divide the $\vec{x_i}$ with the corresponding y_i value is 1 to -1. A hyperplane can be found with the set of points $\vec{x_i}$ using equation $\vec{w}.\vec{x_i} + b = 0$

. Margin is the distance between the hyperplane and the set of points. The aim is to find a hyperplane that maximizes the margin. These margins are defined by the equations 2.15 and 2.16

$$\vec{w}.\vec{x_i} + b <= 1 \tag{2.15}$$

where where y_i = 1

$$\vec{w}.\vec{x_i} + b >= 1 \tag{2.16}$$

where y_i = -1

The distance between these two margins is $2/\vec{w}$

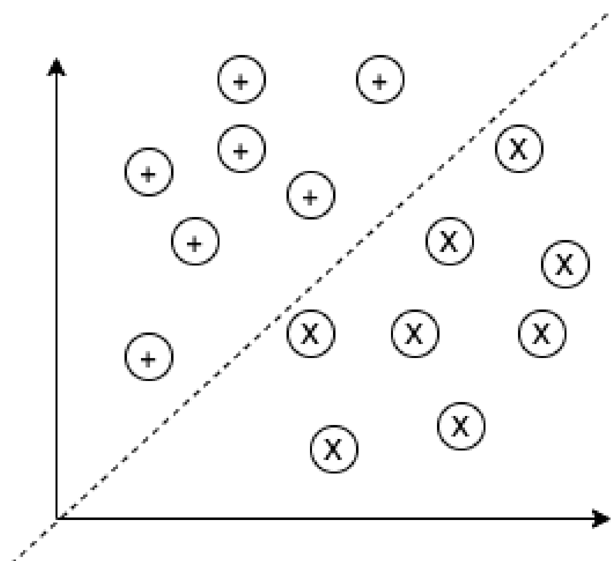

Figure 2.12: SVM Linear classifier

Chapter 3

Data

3.1 Data Collection

In this chapter, we list and describe all the datasets which were collected and used for this project.

A multimodal dataset that consists of EEG, EMG, EKG, Facial video, and GSR is collected for this project. A group of 21 participants (13 male and eight female) is chosen. All the participants are of Indian origin. Out of the 21 participants, 16 are between the ages of 18-24 years, and the remaining five participants are between the ages of 25-34 years. The stimulus is a 13 part video that comprises three parts disgust, three parts humor emotions, and seven parts of neutral videos are chosen as the stimuli. Each of the emotion-induced videos is padded with a neutral video. All the participants are instructed to either freely express, suppress, or reappraise their emotions for both humor and disgust-inducing videos. The order in which they have to perform these regulations for both disgust and humor videos is communicated at the start of the experiment. A reminder is also shown on the screen right before the part of the video is being played. The effect of emotion and participant's intensity is recorded as a ground truth after every part is completed using a keyboard and stored on a computer with the Self-Assessment Manikin (SAM) scale.

3.1.1 Equipment

- GSR data - Two 8mm electrodes are used to collect GSR data, connected to the Biopac system, captured on ACQKnowledge software. The two electrodes are placed on the left-hand palm region.
- EEG data - A quick cap with 32 sensors is used to collect the brain waves captured in Compumedics Neuroscan Curry 8 software. The EEG cap is placed on the head of each participant.
- EKG data - Two 8mm electrodes are used to collect EKG data, connected to the Biopac system, captured on ACQKnowledge software. One electrode is placed on the right shoulder and the other on the

participant's left hip region.

- EMG data - Four 4mm electrodes are used to collect EMG data, connected to the Biopac system, which is captured on ACQKnowledge software. Two electrodes were placed on the top of the right eyebrow and the other two on the participant's left cheek.

- Facial video - A Sony handheld camera is used to collect the facial video. The camera is placed on a tripod stand behind the monitor.

3.1.2 Creating the stimulus

The experiment's stimulus is chosen by looking at some of the most viewed humor videos and disgusting videos on youtube. They are shown to a group of six people asked them to rate the top three disgusting and humorous videos. The videos with the highest votes are selected. These videos are trimmed down to approx 1 min each. Seven neutral videos are used to pad these emotionally induced videos and help decrease emotions' overflow. For neutral, a nature video with relaxing music is selected. The following figures (figure 3.1, 3.2, 3.3, 3.4) show screenshots from each video.

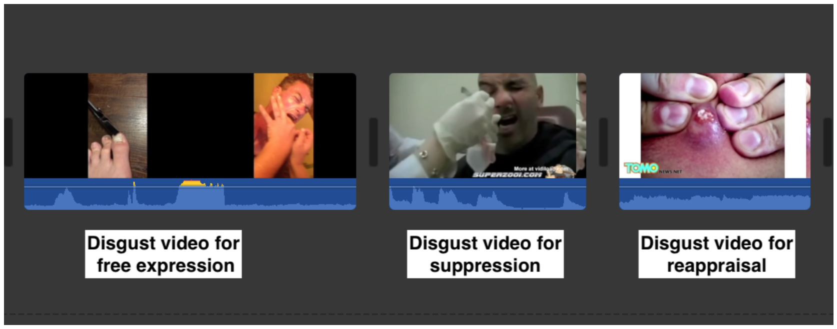

Figure 3.1: A snapshot of the disgust videos that are shown to induce emotions in participants

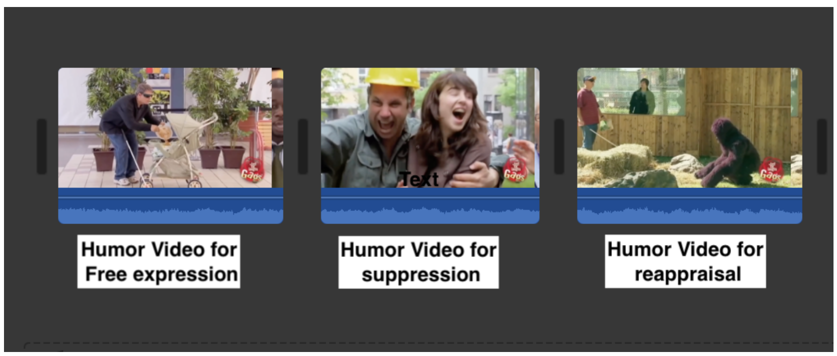

Figure 3.2: A snapshot of the humor videos that are shown to induce emotions in participants

3.1.3 Setting up the participant

Participants who volunteered for this experiment are chosen on a first-come basis in the university. The participants are not paid for this experiment. Most of the participants are either friends or students who took Dr. Nwogu's Computer Vision course. The participants are given a time slot for the experiment. The participants are given a Participant Consent Form and

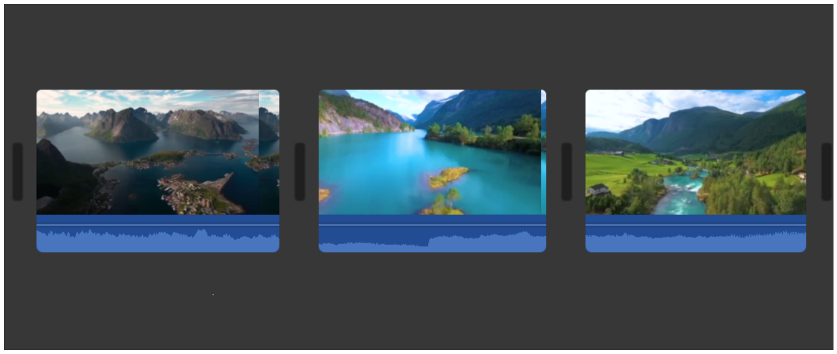

Figure 3.3: A snapshot of the videos that are shown to induce emotions in participants

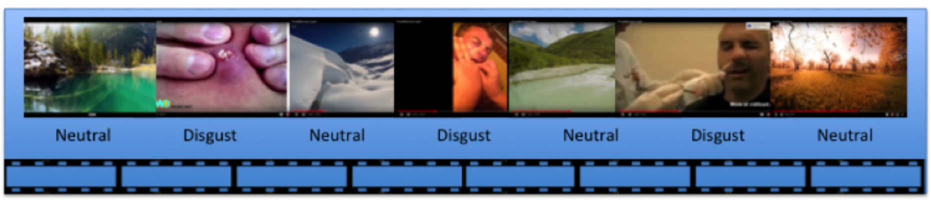

Figure 3.4: A snapshot of the series of disgust along with the neutral videos that are shown to induce emotions in participants

a demographic questionnaire and asked to go through it before signing it. The participant is then brought into the experiment room, and instructions are given to navigate through the process. The participant is prepped by attaching all the sensors. Then they are left alone to watch the video in the experiment room while we monitor the readings from the control room. The image of a participant with all the sensors connected is shown in figure 3.5.

Figure 3.5: Participant with all the sensors connected

Instructions given to the participants

Below are the set of instructions given to the participants before the start of each experiment.

Thank you for accepting to participate in the study.

- Please keep in mind that you can quit the experiment any time you want
- We will be showing a few videos. Please be attentive when the video is playing.
- At any point in time, do not stop watching the video. Do not turn your

face in any other direction. Face towards the monitor always.

- We will be showing you a total of 13 videos.
  - 7 neutral
  - 3 humorous
  - 3 disgusting videos
- There are some signs which you need to get familiarized with before the experiment.
- Express freely(show the sign)
  - When you see this sign, please feel free to express your emotions as you wish
- Reappraise(show the sign)
  - When you see this sign think of a completely different emotion in your brain
  - For example, if you are watching a humorous video think about walking in a crematory at midnight or walking in the forest at midnight, or Assume that a crocodile swallowed your mobile. Your phone is most important to you, and you need to get a mobile

phone. Your best friend is holding the mouth of the crocodile, and now you need to enter and get the mobile phone back

  - If you are watching a disgusting video – think about a funny scene from a movie or comedy series that you love. For example – Mr bean, Joey in Friends, etc

- Suppress(show the sign)
  - Try not to express any emotion.
- Rest(show the sign)
  - You can rest during this time.
- Don't clench your jaw as the signal will be distorted
- Avoid contact with your face during the experiment
- We will also be recording your expression in a video camera. When you start looking at a text, please gently raise your dominant hand.
- Couple of points to keep in mind is
  - Sometimes, the video will pause. Please be seated and look at the screen at all times.

  - Sometimes the screen turns black. Please be seated and look at the screen at all times. Do not move.

- Do you have any questions?

A participant consent form and demographic questionnaire are added in the appendix section.

3.1.4 Data cleaning

- **EEG** The EEG data is collected by the Curry 8 software, which records the readings at every millisecond. These readings are carefully reviewed, and any major distortions are removed. These distortions in the signals can be due to the participant clenching their jaw, touching their head, etc.

  EEG data collected is downloaded in the form of CSV files and downsampled by a factor of 50 from 2000Hz to 40Hz as it is significantly more sampled than is needed for processing. Data is consolidated and grouped according to the emotion and regulation expressed by participants. A median filter is used to smooth the signal. A baseline is extracted for each participant at the end of the first neutral video at the start of the experiment. The remaining data of the participant is normalized to prevent outliers and significant distortions using this baseline. The length of each data sample for each stimulus is made uniform by truncating the extra information collected at the end.

EEG data is also converted into a functional data map. A script is used to convert this entire data into functional data maps. A functional data map is a contour map of the readings at an instance. These maps also have the information sensor location marked in a dark circle along with the readings. These points are removed using K nearest neighbor algorithm. Removing the sensor information and readings will ensure the data will not learn these dark circles when fed to the machine learning models. Each image has a reading which says the maximum and the minimum voltage recorded for the second. Using the max and min voltages, normalized the data (pixels in the image) to prevent outliers. Extra information in the image is removed by cropping and resizing the images to 800*800*3. The images of the functional map before and after is in the figure 3.6 The images are categorized according to the emotion (humor and disgust) and regulation technique (freely express, reappraise and suppress) that the participant performs.

- **GSR and EMG** The GSR and EMG data are also collected in the

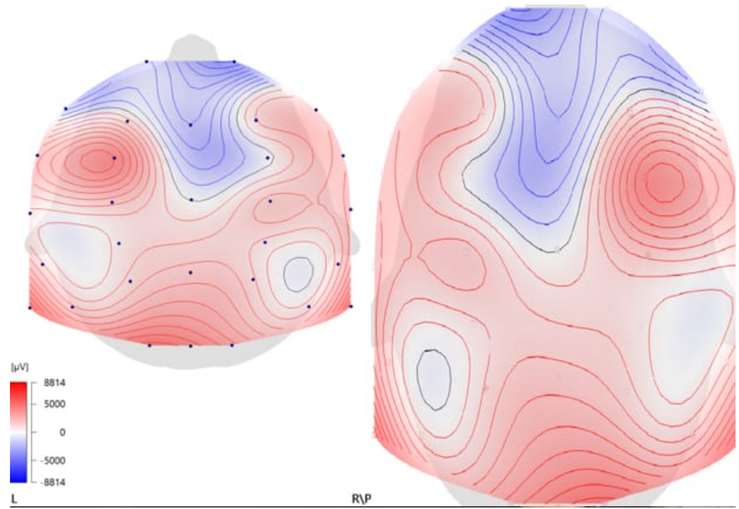

Figure 3.6: Image of the functional data map before (left) and after (right) it is cleaned

form of readings for every millisecond. These readings are exported in a .txt file format. Data is downsampled by 50 from 2000Hz to 40Hz as the data generated is a lot more than the computing capability. The data is then passed through a median filter to smooth the signal and remove sudden abruptions such as eye blinks, eye or hand movements. The data is normalized since the GSR and EMG readings vary for different people. Not all participants are the same; some of them can be highly sensitive to GSR or EMG. To maintain uniformity between all the participants, the data is normalized between 0 and 1. Sometimes the effect of the previous video will tip the scale for the current video. To adjust the readings to provide an even ground, a small window is selected at the end of the neutral video at the start of the experiment and just before the first stimulus is shown. The average for this small window is calculated and is subtracted from the real data. Then the data is parsed and categorized according to the emotion and regulation performed by the participant.

- **EKG** The data cleaning procedure for EKG is similar to GSR and EMG. There is one step which is performed before. EKG is converted to pulse rate by using the inbuilt function given by ACQknowledge software. Then the median filter, normalization, and subtraction of baseline are performed. Data is parsed and categorized according to the emotion and regulation performed by the participant.

3.1.5 Feature Extraction

Galvanic Skin Response Feature extraction is performed for GSR data. The features are mean, mode, standard deviation, entropy, peak detection, rise time, recovery time, maximum peak amplitude, the minimum peak amplitude of GSR values. Peak detection is the gap between the presentation of the stimuli and the onset of the response. Onset is the voltage at which the GSR rapidly rises to reach its peak amplitude. Rise time is the time taken to get back to onset from its peak amplitude. Recovery time is the time the signal takes to reach back to onset from its peak amplitude1. We find the peak onsets and their subsequent offsets and calculate the number of peaks in a two-second window.

Action Units Generally, OpenFace is a software that is used for facial analysis. Unfortunately, in this project, we cannot capture the main action unit (AU9), which is used to determine disgust even when the participants expressed the emotion. The list of 17 FAUs that OpenFace detects is present in table 3.1. Therefore, we used the iMotions emotion FACS (EM-FACS) tool to identify the emotion through the participant's facial expressions.

Table 3.1: Facial action units of OpenFace

AU	Description
AU1	Inner brow raiser
AU2	Outer brow raiser
AU4	Brow lowerer
AU5	Upper lid raiser
AU6	Cheek raiser
AU7	Lid tightener
AU9	Nose wrinkler
AU10	Upper lip raiser
AU12	Lip corner puller
AU14	Dimpler
AU15	Lip corner depressor
AU17	Chin raiser
AU20	Lip stretched
AU23	Lip tightener
AU25	Lips part
AU26	Jaw drop
AU28	Lip suck
AU45	Blink

Chapter 4

Models used

The following are the architectures that are used in this project to achieve the results for our objectives.

4.1 CNN :

The architecture of the CNN model used is taken from VGG19[21] model and tweaked a little bit. The network consists of 16 convolutional layers, four dense layers, three max pooling layers and one softmax layer. After each convolutional layer there is a rectified linear unit as an activation layer. The order of the architecture is as follows: 13 convolutional layers followed by a max pooling, convolutional and max pooling block; this block is repeated one more time, a convolutional layer, four dense layers followed by a softmax layer to classify the result. The hyperparameters used in CNN model are listed in table 4.1

Table 4.1: Architecture of CNN

Description	Value
No of LSTM layers	16
Input size of image	800*800*3
Dense layers	4
Batch size	8
Learning Rate	1e-7
Loss Function	Categorical crossentropy
Optimizer	Stochastic gradient descent (SGD)
No of dropout layers	3
Dropout percentage	0.35
Activation	Rectified linear unit
Classifier	Softmax
Epochs	100

4.2 GRU :

The architecture of GRU model used is three GRU layers followed by two linear layers and a softmax layer to classify at the end. The final parameters we chose for GRU are in the table 4.2.

Table 4.2: Architecture of GRU

Description	Value
No of GRU layers	3
No of hidden layers	100
Input channels	1
Sequence length	100
Fully connected layers	2
Batch size	102
Learning Rate	1e-4
Loss Function	CrossEntropyLoss
Optimizer	Adam

4.3 LSTM :

The architecture of LSTM model used is two LSTM layers followed by three linear layers and a softmax layer to classify at the end. The final parameters we chose for LSTM are in the table 4.3

Table 4.3: Architecture of LSTM

Description	Value
No of LSTM layers	2
No of hidden layers	160
Input channels	1
Sequence length	100
Fully connected layers	3
Batch size	102
Learning Rate	1e-3
Loss Function	CrossEntropyLoss
Optimizer	Adam

Chapter 5

Experiments and results

In this module, we will discuss the experiments we performed and the results we got for our objectives.

5.1 Investigate whether disgust and humor emotions can be classified using EEG and GSR signals

Architecture :

A SVM is used as the model in this classification.

Data :

The GSR data's features that are extracted in section 3.1.5 are used as the input. These include meaning, mode, standard deviation, entropy, peak detection, rise time, recovery time, maximum peak amplitude, minimum peak amplitude. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

Results :

For the humor emotion, the classification rate is 58%, and for disgust, the classification rate is 53%. The confusion matrix of the classification are in the table 5.1.

Table 5.1: Confusion matrix results of SVM

	humor	disgust
humor	0.58	0.42
disgust	0.47	0.53

Observation :

Using GSR data, we can distinguish between humor and disgust with 56% accuracy.

Inference :

- We observed that the features extracted were similar for both emotions because, if someone is highly amused or disgusted, the GSR data fluctuates more. Data fluctuation causes the features (peak detection, ...) to vary. We expected a clear difference between both emotions.

- We expected that the participants would find the stimuli funny and laugh while watching, but we observed that they are not laughing.

5.1.1 Using EEG data and CNN model

Architecture :

The CNN model discussed in 4.1 is used for this classifications.

Data :

The Data for this section is the FD maps that are generated from the EEG data. We have categorized the data according to the emotion and regularization technique performed by the participants. The following are the total number of FD maps available concerning each category that is used. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

- Disgust emotion : 4150
- Humor emotion : 5160

For model, distinguishing between disgust and humor the data is divided as below

- Training: 4000
- Testing: 676

- Validation: 1285

Results :

For the humor emotion the classification rate is 62% and for disgust the classification rate is 59%. The confusion matrix of the classification are in the table 5.2.

Table 5.2: Confusion matrix results of CNN

	humor	disgust
humor	0.62	0.38
disgust	0.41	0.59

Observation :

Using EEG data, we can distinguish between humor and disgust 61% of the time.

Inference :

EEG is a better signal to distinguish between emotions compared to GSR data.

5.2 Develop computational models and visualization schemes to analyze the three emotion regulation strategies using different modalities

5.2.1 Using EEG humor data and CNN model

Architecture :

The architecture of the CNN used for this classification is described in section 4.1.

Data :

Data used are the FD maps that are generated from the EEG experiment. Following are the total sample size available with respect to each category. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

- Humor freely express: 2074
- Humor suppress: 1801
- Humor reappraisal: 1285

The total sample is divided into training, testing and validation as follows.

- Training: 4100

- Testing: 500
- Validation: 560

Results :

For free expression the classification rate is 50%, for suppress classification rate is 20% and for reappraisal the classification rate is 44%. The confusion matrix of the classification are in the table 5.3.

Table 5.3: Confusion matrix results of CNN for EEG humor

	freely express	suppress	reappraisal
freely express	0.50	0.14	0.36
suppress	0.38	0.20	0.42
reappraisal	0.41	0.15	0.44

Observation :

The model got confused between freely express and reappraisal. Suppress is always classified as either freely express or reappraisal.

Inference :

The whole-brain image is used to differentiate between emotions regulations strategies. We found some research has much higher accuracy when compared if they used a particular part of the brain for each emotion.

5.2.2 Using EEG disgust data and CNN model

Architecture :

The architecture of the CNN used for this classifications is described in section 4.1.

Data :

Data used are the FD maps that are generated from the EEG experiment. Following are the total sample size available with respect to each category. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

- Disgust freely express: 1070
- Disgust suppress: 1422
- Disgust reappraisal: 1658

The total data is divided into training, testing and validation as follows.

- Training: 3300
- Testing: 400
- Validation: 450

Results :

For free expression the classification rate is 38%, for suppress classification rate is 42% and for reappraisal the classification rate is 67%. The confusion matrix of the classification are in the table 5.4.

Table 5.4: Confusion matrix results of CNN for EEG disgust

	freely express	suppress	reappraisal
freely express	0.38	0.30	0.32
suppress	0.21	0.42	0.37
reappraisal	0.18	0.15	0.67

Observation :

The model can classify reappraisal (67%) much better than the other two categories. It is not able to classify freely express, and mistakes suppress to be reappraisal by 37%.

Inference :

The whole-brain image is used to differentiate between emotions regulations strategies. We found some research has much higher accuracy when compared if they used a particular part of the brain for each emotion.

5.2.3 Using GSR humor data and GRU model

Architecture :

The architecture of the GRU used for this classifications as described in section 4.2.

Data:

The humor GSR data denoised with a median filter, the sample stride length of 100 (approx 5 seconds), is chosen. The total number of samples that we got is 1020 per emotion regulation type. These samples are used as the input to train and test the GRU. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

Results :

For free expression the classification rate is 36%, for suppress classification rate is 14% and for reappraisal the classification rate is 34%. The confusion matrix of the classification are in the table 5.5.

Table 5.5: Confusion matrix results of GRU for GSR humor

	freely express	suppress	reappraise
freely express	0.36	0.12	0.45
suppress	0.41	0.14	0.38
reappraise	0.45	0.14	0.34

Observation :

The model is not able to classify any emotion regulation. It got confused with freely express and reappraisal the majority of the time.

Inference :

There is some research currently going on at Stanford University by Dr. Gross's group[17]. According to it, the emotion regulation strategies work well only with negative emotions. In the above model, we observed the same where the classification did not happen.

5.2.4 Using GSR disgust data and GRU model

Architecture :

The architecture of the GRU used for this classifications as described in section 4.2.

Data :

The disgust GSR data, which is denoised with a median filter, is chosen for the sample stride length of 100 (approx 5 seconds). The total number of samples that we got is 1020 per emotion regulation type. These samples are used as the input to train and test the GRU. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

Results :

For free expression the classification rate is 19%, for suppress classification rate is 38% and for reappraisal the classification rate is 68%. The confusion matrix of the classification are in the table 5.6.

Table 5.6: Confusion matrix results of GRU for GSR disgust

	freely express	suppress	reappraise
freely express	0.19	0.31	0.49
suppress	0.26	0.38	0.35
reappraise	0.20	0.12	0.68

Observation :

The model can classify reappraisal better and suppress by a slight margin. Freely express is mostly classified as either suppress or reappraisal.

5.2.5 Using GSR humor data and LSTM model

Architecture :

The architecture of the LSTM used for this classifications is described in section 4.3.

Data :

The disgust GSR data, which is denoised with a median filter, is chosen for the sample stride length of 100 (approx 5 seconds). The total number of samples that we got is 1020 per emotion regulation type. These samples are used as the input to train and test the LSTM. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

Results :

For free expression the classification rate is 32%, for suppress classification rate is 25% and for reappraisal the classification rate is 22%. The confusion matrix of the classification are in the table 5.7.

Table 5.7: Confusion matrix results of LSTM for GSR disgust

	freely express	suppress	reappraise
freely express	0.32	0.32	0.36
suppress	0.46	0.25	0.29
reappraise	0.48	0.30	0.22

Observation :

Model is not able to classify any emotion regulation strategy.

Inference :

There is some research currently going on at Stanford University by Dr. Gross's group[17]. According to it, the emotion regulation strategies work well only with negative emotions. In the above model, we observed the same where the classification did not happen.

5.2.6 Using GSR disgust data and LSTM model

Architecture :

The architecture of the LSTM used for this classifications is described in section 4.3.

Data :

The disgust GSR data, which is denoised with a median filter, is chosen for the sample stride length of 100 (approx 5 seconds). The total number of samples that we got is 1020 per emotion regulation type. These samples are used as the input to train and test the LSTM. Five-fold cross-validation is used to determine the training, testing sets for the model to learn.

Results :

For free expression the classification rate is 6%, for suppress classification rate is 34% and for reappraisal the classification rate is 64%. The confusion matrix of the classification are in the table 5.8.

Table 5.8: Confusion matrix results of LSTM for GSR disgust

	freely express	suppress	reappraise
freely express	0.06	0.46	0.48
suppress	0.29	0.34	0.37
reappraise	0.18	0.18	0.64

Observation :

Model is able to classify reappraise better than both suppress and freely express. Freely express is mostly classified as suppress and reappraise and not able to recognize suppress.

5.2.7 Prefrontal cortex

Data :

The FP1 and FP2 sensor data that is collected as part of EEG disgust is used. Data is down sampled by a factor of 50. A median filter is applied on the data to smoothen the signal. Mean of all the participants FP1 and FP2 sensor data is then plotted on the graph

Plots : In the following figure 5.1 the graph between the two dark lines parallel to the Y-axis is the part where the participants are watching the emotion-induced stimulus. To the left and to the right of the dark lines participants are watching neutral videos.

Observation :

- We are able to observe the clear difference between both regulation strategies.

- We also observed that the reappraisal manifested in the early part of

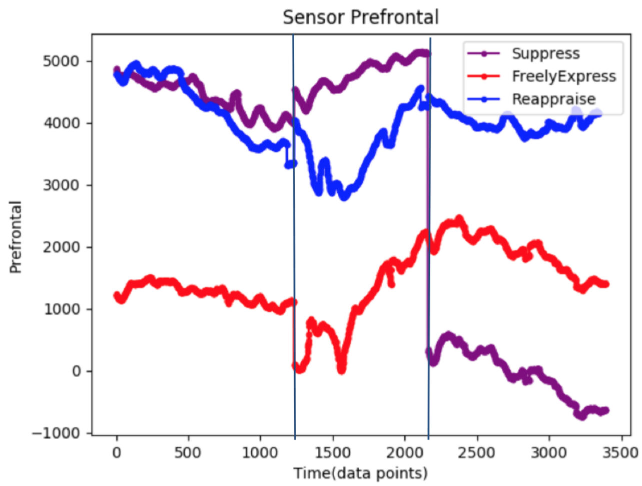

Figure 5.1: Prefrontal Disgust EEG data

stimuli similar to Gross's work [11]. Suppression did not manifest at the later part.

5.2.8 Comparison of pulse rate

Data:

The Data that is used for this section is the EKG. In section 3, we extracted the heart rate (beats per minute) from EKG data.

Plots :

The below plots 5.2 and 5.3 are the change scores of mean heart rate for all 21 participants. The time interval between two data points on the x-axis is one second. In the graphs, the two dotted lines parallel to the Y-axis where the participants are watching the emotion-induced stimulus. To the left and the right of the dotted lines, participants are watching neutral videos.

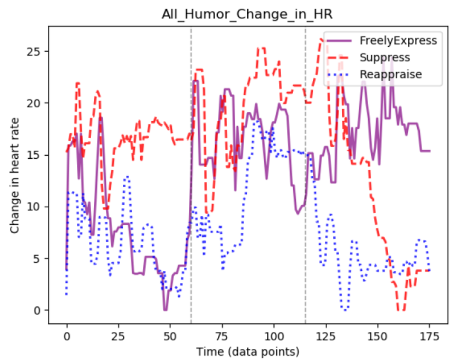

Figure 5.2: Change in mean heart rate - humor

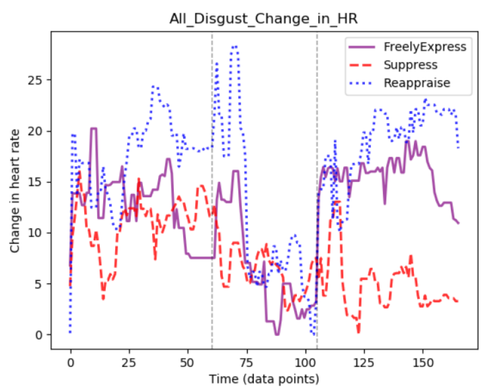

Figure 5.3: Change in mean heart rate - disgust

Observation :

The heart rate is highest for disgust in emotional reappraisal followed by freely express and suppression. For humor the heart rate for suppression is higher than the freely express and reappraisal. We observed that in disgust, the reappraisal is higher for the initial part, and then the distinguishing factor wears off.

A notable observation here is, in the previous work [8], disgust stimuli generally reduce the heart rate of the participants while watching, which points that the reappraisal reduced the effect of disgust stimulus by increasing the heart rate, unlike suppression.

5.2.9 Using facial videos

Data :

The AUs that are obtained from section 3.1.5 is used in the Facial Expression Analysis module of the iMotions tool. The iMotions analyzes a set of points on the face to determine the participant's emotion at a particular point in time. We calculated the humor and disgust emotions of the participants and plotted them in Figures 5.4 and 5.5. In these plots, each data point represents 0.1 seconds.

Plots :

In the graphs, between the two dotted lines parallel to Y axis is the part where the participants are watching the emotion induced stimulus. To the left and to the right of the dotted lines participants are watching neutral videos.

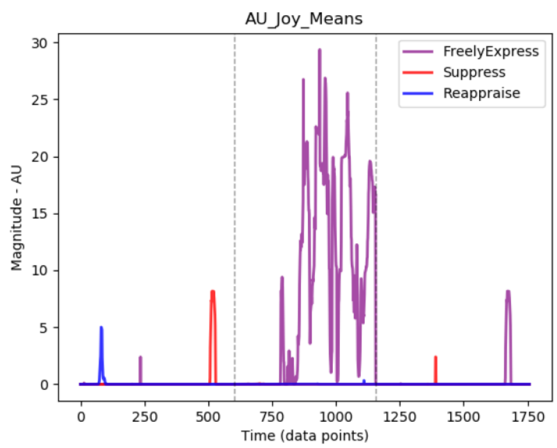

Figure 5.4: Humor emotion visualization

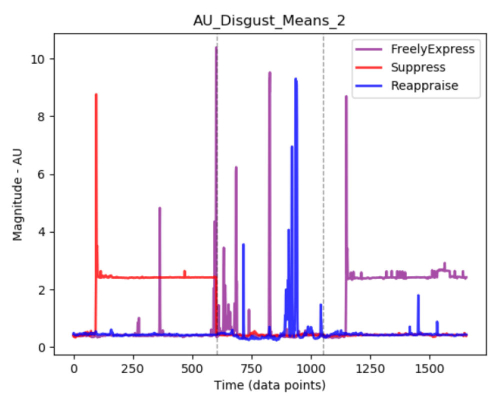

Figure 5.5: Disgust emotion visualization

Observation : While watching humor stimuli, the participants could successfully reappraise, suppress and freely express their emotions. While watching disgust stimuli, participants can regulate their emotions, mostly barring some instances.

5.2.10 Self reporting results

During the experiment, all the participant's (n = 21) emotion's valence and intensity of the emotion after each regulation technique. The data from all the participants are aggregated and shown in Tables 5.9 and 5.10.

Table 5.9: Statistics from self-reported measures (humor)

	Humor valence	Humor Intensity
Reappraisal Mean	4.4	4.35
Reappraisal Std dev	1.39	1.63
Suppression Mean	4.8	3.75
Suppression Std dev	1.06	1.80
Freely express Mean	5.55	4.45
Freely express Std dev	1.19	2.03

Table 5.10: Statistics from self-reported measures (disgust)

	Disgust valence	Disgust Intensity
Reappraisal Mean	3.29	4.67
Reappraisal Std dev	1.42	1.83
Suppression Mean	3.19	4.57
Suppression Std dev	1.59	1.68
Freely express Mean	2.67	4.95
Freely express Std dev	1.36	1.36

We also performed the t-test to find evidence of a significant difference between suppression and reappraisal. The t-value measures the size of the difference relative to the variation in your sample data. If P-value is closer to 0.05, we can say that the two classes are different. The data used to perform the t-test is the difference in the self-reporting results of neutral video participants watched before the emotion-induced stimulus. The change in valence and intensity is used to calculate the p-value.

The P-value for humor valence suppression and reappraisal is 0.466, showing that the two classes are not different. Comparison is made in the table 5.11

Table 5.11: T test for the valence of suppression and reappraisal for humor emotion

	Humor Suppression	Humor Reappraisal
Mean	-0.333	-0.619
Variance	1.233	2.047
Observations	21	21
Pearson Correlation	0.052	
Hypothesized Mean Difference	0	
df	20	
t Stat	0.741	
P(T¡=t) one-tail	0.233	
t Critical one-tail	1.724	
P(T¡=t) two-tail	0.466	
t Critical two-tail	2.085	

P value for disgust valence suppression and reappraisal is 0.925, showing that the two classes are not different. Comparison is made in the table 5.12

Table 5.12: T test for the valence of suppression and reappraisal for disgust emotion

	Disgust Suppression	Disgust Reappraisal
Mean	-1.857	-1.904
Variance	4.028	5.690
Observations	21	21
Pearson Correlation	0.466	
Hypothesized Mean Difference	0	
df	20	
t Stat	0.0952	
P(T¡=t) one-tail	0.462	
t Critical one-tail	1.724	
P(T¡=t) two-tail	0.925	
t Critical two-tail	2.085	

P value for disgust arousal suppression and reappraisal is 0.584, showing that the two classes are not different. Comparison is made in the table 5.13 P value for disgust arousal suppression and reappraisal is 0.07, showing that the two classes are different with a 90% confidence level. Comparison is made in the table 5.14

Results are not as significant compared to behavioral and physiological measures. Only the disgust arousal shows the difference between the two emotion regulation strategies. We understood that some of the participants were confused by the self-reporting tool's expectations. Quantifying the level of emotional valence and intensity in the middle of the experiment may not be

Table 5.13: T test for the arousal of suppression and reappraisal for humor emotion

	Humor Suppression	Humor Reappraisal
Mean	-0.428	-0.047
Variance	4.457	4.247
Observations	21	21
Pearson Correlation	-0.131	
Hypothesized Mean Difference	0	
df	20	
t Stat	-0.556	
P(T¡=t) one-tail	0.292	
t Critical one-tail	1.724	
P(T¡=t) two-tail	0.584	
t Critical two-tail	2.085	

the most effective way to obtain the data.

Table 5.14: T test for the arousal of suppression and reappraisal for humor emotion

	Disgust Suppression	Disgust Reappraisal
Mean	0.142	-0.857
Variance	4.228	5.428
Observations	21	21
Pearson Correlation	-0.402	
Hypothesized Mean Difference	0	
df	20	
t Stat	1.902	
P(T¡=t) one-tail	0.035	
t Critical one-tail	1.724	
P(T¡=t) two-tail	0.071	
t Critical two-tail	2.085	

5.2.11 Using EMG measures

Data :

Corrugator data collected from the participants is used in this section, and we were not able to obtain a reliable signal from the zygomaticus muscle. Corrugator muscles are activated when expressing disgust which calculates the AU4 (lowering eyebrow). Furthermore, Rymarczyk et al.[20] showed that disgust causes activity in the corrugator supercilii muscle. Figure 5.6 below shows the aggregation of corrugator from all the participants.

Results :

The two dotted lines parallel to Y-axis are where the participants are watching the emotion-induced stimulus in the graphs. To the left and the right of the dotted lines, participants are watching neutral videos.

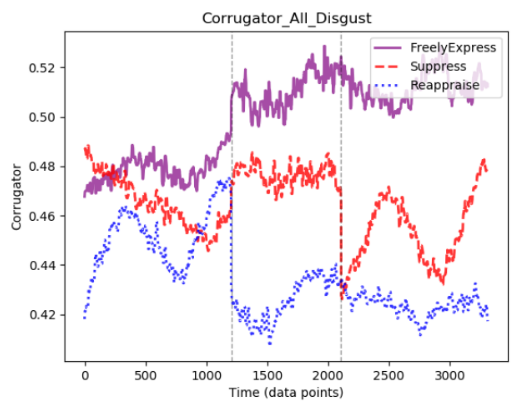

Figure 5.6: EMG readings from electrodes at the corrugator muscle for three emotion regulation type for disgust across all the participants

We also calculated a t-test for the change in the mean for reappraisal and suppression. T-test shows a minimal difference between both the emotion regulation strategies. The results are in the table 5.15.

Observation :

The signal is lower for the participants when reappraising but significant when they are freely expressing. We saw a slight reduction when the participants are suppressing, indicating that reappraisal has some different results

Table 5.15: T test for the EMG data of suppression and reappraisal for disgust emotion

	Disgust Suppression	Disgust Reappraisal
Mean	0.11	-0.0256
Variance	0.0012	0.004
Observations	17	17
Pearson Correlation	-0.4977	
Hypothesized Mean Difference	0	
df	15	
t Stat	1.67952	
P(T¡=t) one-tail	0.056	
t Critical one-tail	1.753	
P(T¡=t) two-tail	0.1137	
t Critical two-tail	2.131	

than suppression.

Chapter 6

Conclusion

6.1 Conclusion

EEG is very good at determining emotion. GSR calibrates the emotional intensity and is not used to classify the emotion type. In the first experiment, Sections 5.1.1 and 5.1.2, we tried to distinguish the participants' emotions. EEG did relatively better with an accuracy of 61% compared to GSR's accuracy of 55%.

Classifying the emotion regulation for disgust, using EEG and CNN, the model could classify better than any other models. The reappraisal being the stand out of all the emotions in terms of accuracy. Using LSTM, GRU, and GSR data, the reappraisal stood out again. The classification is not so great for freely express. The difference in reappraisal and suppression was even observed behaviorally (EMG and facial analysis). The facial analysis plots identify the participants' expression is higher for disgust which aligns with the previous work, and they failed to reappraise for disgust emotion after some time. Generally, it is harder to reappraise the disgust emotion than any humor/fun emotion. We can distinguish between both regulation strategies using EKG data plots. We could not compare the results with self-reporting as we discussed before because they are not reliable based on the participants' conversations. All of this points out that reappraisal is significantly different from suppression or freely express.

Classifying emotion regulation for humor, using EEG and CNN, the model could classify freely express and reappraisal but did not organize the suppress. With LSTM, GRU, and GSR data, the model did not predict any emotional regulation strategy. The FAU analysis shows us that the participants suppressed and reappraised their emotions successfully. The GRU model could not classify the emotion due to either a low intensity of the initial emotion or a similar intensity of emotion regulation strategies. We can observe the heart rate for humor does not represent a clear difference between the regulation strategies.

6.2 Limitations

All the participants are of Indian origin. Out of the 21 participants who participated in the survey, 76% are between the ages of 18-24 years, and the remaining 24% are between the ages of 25-34 years.

6.3 Future Work

Classify the emotion regulation techniques by using two or more input streams (EEG and GSR) and check if the model can perform better. The participant's size can be increased(more than 21 participants) and can include a diverse group of participants in the study to get the results that are not biased—also using more advanced machine learning models to classify the emotion regulation.

Appendices

.1 Appendix A - Participant Consent form

Computational Methods for Analyzing Emotion Regulation using Multimodal Data

Participant Consent Form

Principal investigator: Geeta Madhav Gali, Abby Melake, Ifeoma Nwogu

Introduction:

We are conducting this study in order to better understand how people's stimuli respond when emotions are regulated while watching a video. You will be asked to view a series of videos and express freely, reappraise and suppress your emotions. We are also interested in your feedback after every video to rate the emotion and intensity of the emotion you felt. Over the course of the experiment, your body's responses will be monitored with sensors that will be taped to your skin and head.

Procedure:

This study will involve about one hour of your time spent in the lab. At the beginning of the study you will be asked some demographics questions and asked to complete a short questionnaire about different behaviors related to attention. The experimenter will attach sensors to your skin in order to measure your body's responses. One sensor will be attached to your right collarbone and lower left abdomen, two on your non-dominant hand. The scalps will be prepped with rubbing alcohol and a mild skin abrasive gel and then fitted with a cap embedded with sensors. EEG activity will be collected using a cap with 32 sensors, which are placed using the 10-20 International System (Klem et al., 1999). Sensors will also be placed behind each ear on the mastoid bone, above and below the left eye, directly to the side of the left eye, directly to the side of the right eye, and on the left earlobe using medical adhesive tape (similar to a band-aid).

At this point, you will be asked to watch to 14 videos blocks. During each block please follow the necessary protocol (Freely expressing the emotion or Suppressing or Reappraising). After each block you will be asked to rate yourself on emotion and the intensity of the emotion. Please answer it as accurate as possible. Please do your best to regulate your emotion and focus on the task at hand.

Risks and Benefits:

By participating in this study, you will benefit by gaining experience as a research subject and learning more about psychological research. The information gathered from this study may give us information on how the human stimuli responds when emotions are regulated.

There are a few minor risks that may come from participating in this study. First, there may be some minor discomfort while the sensors are placed on you, and when the sensors are taken off there may be some red marks left over that will go away within a couple of hours. There may be some discomfort when watching disgust videos, but we will end with watching a series of amusing videos which will help you get over the discomfort. Another potential risk is that you might feel fatigued during the course of the laboratory assessment as your continuous attention is required. To prevent this from happening breaks will be offered. A final risk is discomfort from the EEG cap, during both preparation and the laboratory assessment but great care will also be taken in ensuring that the participant is not in any discomfort during the course of the assessment.

Some of the videos that you will be watching are considered disgusting. For example, surgical procedures such as pulling a tooth out of a person. In case of any discomfort, please contact RIT counseling center, (585) 475-2261 during business or (855) 436-1245 hours after business hours, weekends / holidays.

Confidentiality:

Your responses during the sessions will be confidential to the extent allowed by the law. Confidentiality will be accomplished by storing your data under a letter and number code. The copy of the consent form that you will sign will be kept in a cabinet in Dr. Nwogu's office with limited card swipe access. All data will be presented in aggregated form, and your name will not be used when data from the study are published.

Incentives:

There is no incentive for participating in the research.

Your Rights as a Research Participant:

Participation is voluntary. Your decision to participate or not to participate will in no way affect your job, school, or student status. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled, and it will not harm your relationship with student researchers or Dr. Ifeoma Nwogu. You may stop at any point with no consequences. Simply inform the researcher you wish to stop, and you may leave.

Contacts for Questions of Problems:

Contact Geeta Madhav Gali gg6549@rit.edu or Dr. Ifeoma Nwogu at ion@cs.rit.edu if you have questions about the study, any problems, unexpected physical or psychological discomforts, any injuries, or you think that something unexpected is happening. If you have any concerns, are feeling distressed or troubled you may contact the counseling center here at RIT at (585) 475-2261.

Contact Heather Foti, Associate Director of the HSRO at (585) 475-7673 or hmfsrs@rit.edu if you have any questions or concerns about your rights as a research participant.

By signing below, I confirm that I am at least 18 years old and have read the information about the study and the equipment being used. I understand the information and have had the opportunity to ask questions about the experiment.

I understand that I may ask for the experiment to be terminated at any time.

Signature ____ Date______________

Name (please print)____

In order to advance the science and encourage repeatability, the data collected from this experiment could be shared with other researchers to test the validity of the measurements. Such researchers will be required to sign a consent form before being given access to the data, including face images, facial expressions, Heartrate, EEG from brain and GSR readings.

I hereby also grant permission for my anonymized data to be made available to other researchers.

Yes ☐ No ☐

Signature ____ Date______________

Name (please print)____

.2 Appendix B - Demographics Questionnarie

Demographics Questionnaire- Computational Methods for Analyzing Emotion Regulation using Multimodal Data

What is your Gender?

- ☐ Male
- ☐ Female
- ☐ Other

What is your Age?

- ☐ Under 18 years old
- ☐ 18-24 years old
- ☐ 25-34 years old
- ☐ 35-44 years old
- ☐ 45-54 years old
- ☐ 55-64 years old
- ☐ 65-74 years old
- ☐ 75 years or older

What is your Ethnicity?

- ☐ White
- ☐ Hispanic or Latino
- ☐ Black or African American
- ☐ Native American or American Indian
- ☐ Asian
- ☐ Other

.3 Appendix C - Conversations with Curry support team

RIT

Geeta Madhav Gali <gg6549@g.rit.edu>

Contact Submission from Madhav Gali via Compumedics Neuroscan Website

11 messages

Compumedics Neuroscan Support <sales@compumedicsneuroscan.com> Mon, Feb 4, 2019 at 9:00 AM
To: gg6549@rit.edu
Cc: techsup@neuroscan.com

From:
Madhav Gali
Rochester Institute of Technology
Computer Science
1 Lomb Memorial Drive
Rochester
14623
United States
gg6549@rit.edu
5854353011

Message Body:
Hi

I am working on the collecting EEG data. I was able to see the FD map after. I am wondering if there is a way to generate FD maps for every milli second or every second and download the FD map images at once, instead of moving over to that time and downloading each FD map image individually.

Thanks

Use of information:
Yes, I agree the data provided in this form may be shared with a local Compumedics Neuroscan representative in my region.

This mail is sent via the Compumedics Neuroscan Website
http://compumedicsneuroscan.com

Caitlin Melton <cmelton@compumedicsusa.com> Mon, Feb 4, 2019 at 10:36 AM
To: "gg6549@rit.edu" <gg6549@rit.edu>
Cc: Tech Sup <techsup@neuroscan.com>

Hello Madhav,

Could you clarify a few details for us about your question? Which software are you using to collect and view your EEG data, Curry or Scan? Please let us know which version of the software you are using as well (Ie if Curry, tell us if it is Curry 7 or 8 and which build it is. This information can be found in the lower left hand corner of your Curry program.) Also, when you refer to FD maps are you referring to Frequency Domain maps or Functional Data maps?

Thank you,

Caitlin Melton

Clinical/Research Application Support Analyst

Compumedics Neuroscan

Main 877.717.3975

Direct 704.749.3222

Support 704.749.3202

Fax 704.749.3299

[Quoted text hidden]

Geeta Madhav Gali <gg6549@g.rit.edu> Mon, Feb 4, 2019 at 12:26 PM
To: Caitlin Melton <cmelton@compumedicsusa.com>
Cc: techsup@neuroscan.com

Hi Ms Melton,

Thank you for reaching out to me. I am using Curry 8. When I said FD map I am referring Function Data map. Please reach out to me if you need any more information.

Have a great day.

Thanks and regards
Madhav Gali

> On Feb 4, 2019, at 10:36 AM, Caitlin Melton <cmelton@compumedicsusa.com> wrote:
>
> Hello Madhav,
>
> Could you clarify a few details for us about your question? Which software are you using to collect and view your EEG data, Curry or Scan? Please let us know which version of the software you are using as well (Ie if Curry, tell us if it is Curry 7 or 8 and which build it is. This information can be found in the lower left hand corner of your Curry program.) Also, when you refer to FD maps are you referring to Frequency Domain maps or Functional Data maps?
>
> Thank you,
> Caitlin Melton
> Clinical/Research Application Support Analyst
> Compumedics Neuroscan
> Main 877.717.3975
> Direct 704.749.3222
> Support 704.749.3202
> Fax 704.749.3299
>
> <image001.jpg>

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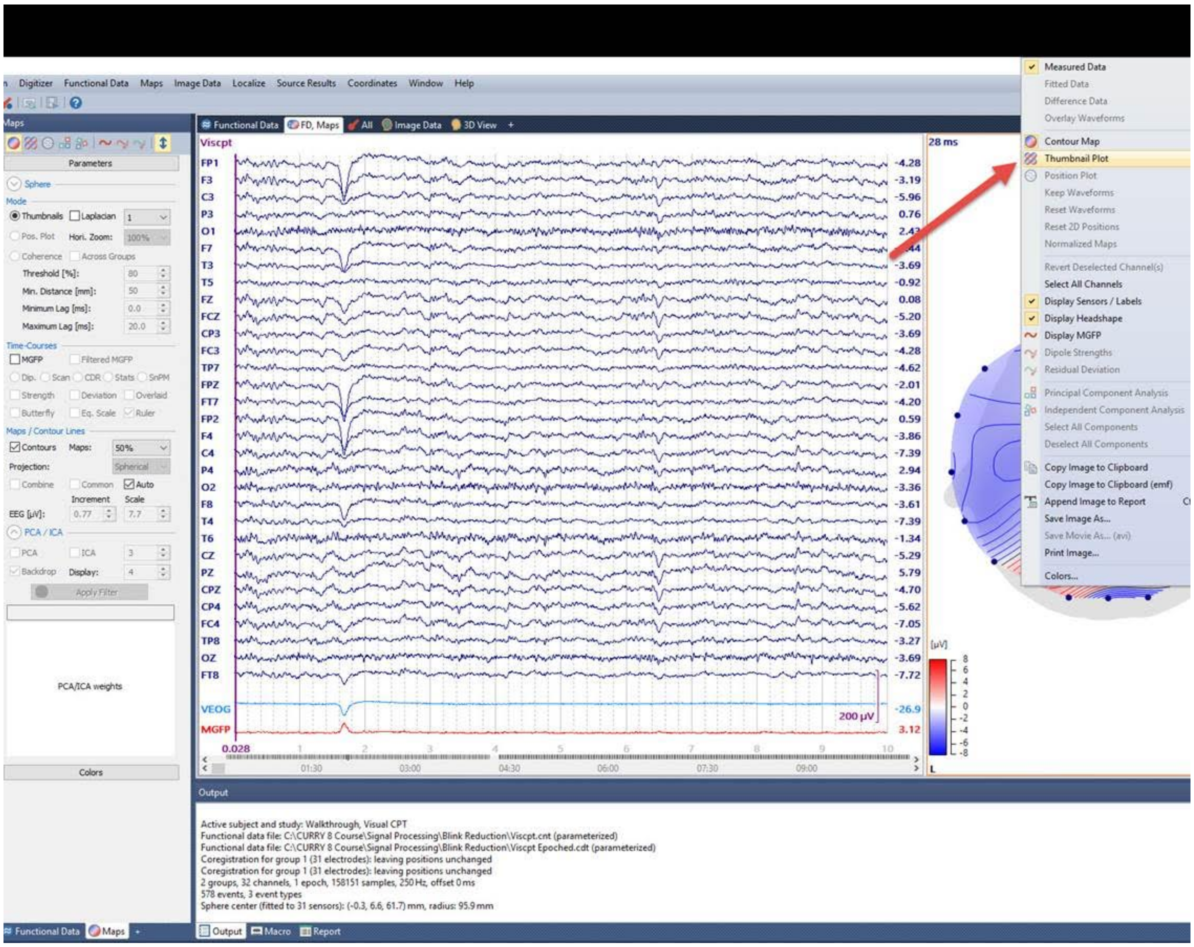
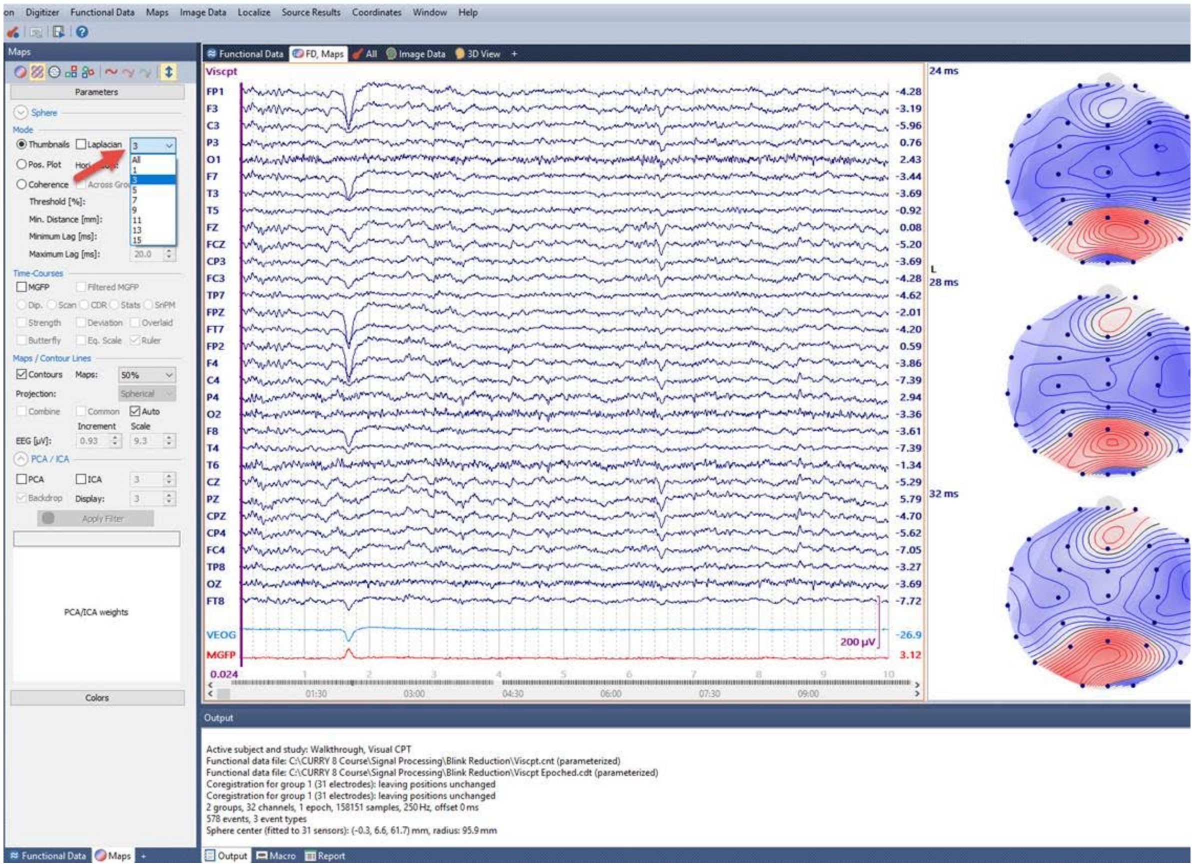
Caitlin Melton <cmelton@compumedicsusa.com>
To: Geeta Madhav Gali <gg6549@rit.edu>

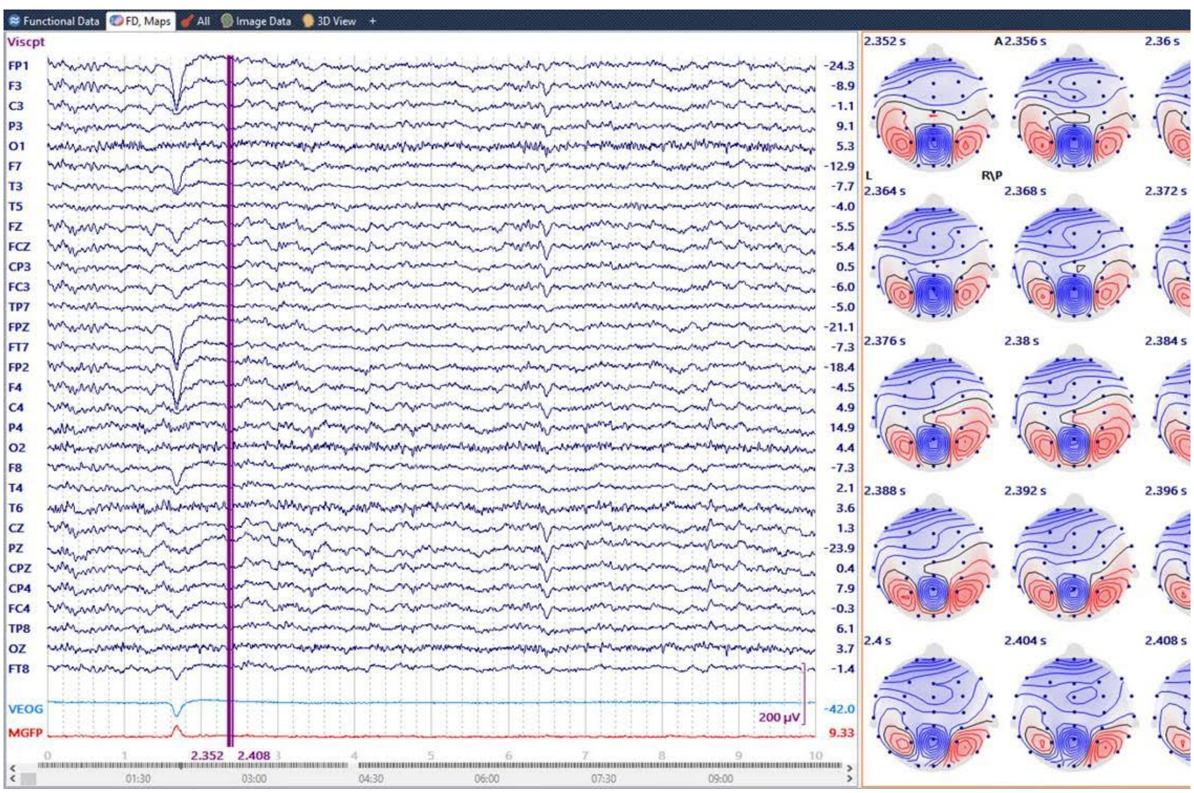
Mon, Fel

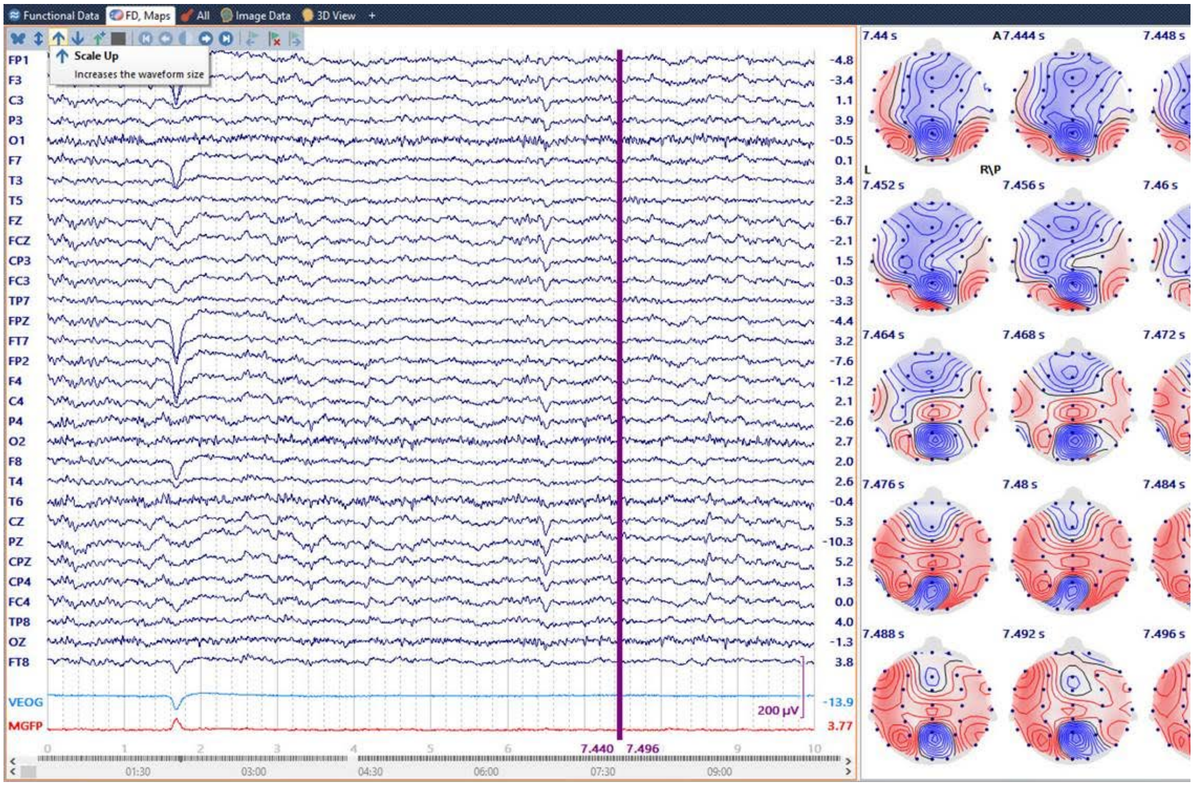
Hi Madhav,

There is a way for you to see multiple FD maps by using the thumbnail plot instead of just the contour map. Please see the pictures below for reference. You can change the amount of thum shown at a time in the Maps menu and if you move your cursor across your EEG data you can go through and save each group of pictures.




Digitizer Functional Data Maps Image Data Localize Source Results Coordinates Window Help
Functional Data
FD, Maps
All
Image Data
3D View
Viscpt
FP1 F3 C3 P3 O1 F7 T3 T5 FZ FCZ CP3 FC3 TP7 FPZ FT7 FP2 F4 C4 P4 O2 F8 T4 T6 CZ PZ CPZ CP4 FC4 TP8 OZ FT8
VEOG
MGFP
200 µV
24 ms
28 ms
32 ms
PCA/ICA weights
Colors
Output
Active subject and study: Walkthrough, Visual CPT
Functional data file: C:\CURRY 8 Course\Signal Processing\Blink Reduction\Viscpt.cnt (parameterized)
Functional data file: C:\CURRY 8 Course\Signal Processing\Blink Reduction\Viscpt Epoched.cdt (parameterized)
Coregistration for group 1 (31 electrodes): leaving positions unchanged
Coregistration for group 1 (31 electrodes): leaving positions unchanged
2 groups, 32 channels, 1 epoch, 158151 samples, 250 Hz, offset 0 ms
578 events, 3 event types
Sphere center (fitted to 31 sensors): (-0.3, 6.6, 61.7) mm, radius: 95.9 mm
Output
Macro
Report


Functional Data
FD, Maps
All
Image Data
3D View
Viscpt
FP1 F3 C3 P3 O1 F7 T3 T5 FZ FCZ CP3 FC3 TP7 FPZ FT7 FP2 F4 C4 P4 O2 F8 T4 T6 CZ PZ CPZ CP4 FC4 TP8 OZ FT8
VEOG
MGFP
200 µV
2.352
2.408
2.352 s
2.356 s
2.36 s
2.364 s
2.368 s
2.372 s
2.376 s
2.38 s
2.384 s
2.388 s
2.392 s
2.396 s
2.4 s
2.404 s
2.408 s



Please let me know if you need any other assistance!

Thank you,

Caitlin Melton

Clinical/Research Application Support Analyst

Compumedics Neuroscan

Main 877.717.3975

Direct 704.749.3222

Support 704.749.3202

Fax 704.749.3299

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> Sleep Diagnostics > Neurodiagnostics > Brain Research > Doppler Sonography > Medical Innovations

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Geeta Madhav Gali <gg6549@g.rit.edu> Mon, Feb 4, 2019 at 3:02 PM
To: Caitlin Melton <cmelton@compumedicsusa.com>
Cc: Geeta Madhav Gali <gg6549@rit.edu>

May be I did not communicate properly.

The project that I am currently working need Images(FD maps) to be fed into a machine learning model. Here are the steps that I am following
1. I collect the EEG data for a period of 14 minutes.
2. Once I did that, I need to generate 14 *60(1 image(FD map) for each second) images.
The procedure that I knew until now is manually navigating to each second in the data that I collected and downloading the image(FD map). But is there a feature in the Curry 8 where I can click a button or do something so that I can get all the images(14* 60 which is 840 images) at once? This is my question.

Please let me know.

Thanks and regards
Madhav Gali

On Feb 4, 2019, at 2:40 PM, Caitlin Melton <cmelton@compumedicsusa.com> wrote:

Hi Madhav,

There is a way for you to see multiple FD maps by using the thumbnail plot instead of just the contour map. Please see the pictures below for reference. You can change the amount of thumbnail plots you are shown at a time in the Maps menu and if you move your cursor across your EEG data you can go through and save each group of pictures.

<image006.jpg>

<image007.jpg>

<image008.jpg>

<image009.jpg>

Please let me know if you need any other assistance!

Thank you,
Caitlin Melton
Clinical/Research Application Support Analyst
Compumedics Neuroscan
Main 877.717.3975
Direct 704.749.3222
Support 704.749.3202
Fax 704.749.3299

<image001.jpg>

[Quoted text hidden]

Caitlin Melton <cmelton@compumedicsusa.com> Mon, Feb 4, 2019 at 3:17 PM
To: Geeta Madhav Gali <gg6549@rit.edu>
Cc: Curry8 Help <Curry8help@neuroscan.com>

Hi Madhav,

I am including our Curry team in the email chain and they will know of if there is an easier way to accomplish what you need. They are based in Hamburg, Germany and will reach out when they get back to their offices. Note they are in a different time zone, sorry for any inconvenience this causes.

Thank you,

Caitlin Melton

Clinical/Research Application Support Analyst

Compumedics Neuroscan

Main 877.717.3975

Direct 704.749.3222

Support 704.749.3202

Fax 704.749.3299

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> Sleep Diagnostics > Neurodiagnostics > Brain Research > Doppler Sonography > Medical Innovations

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[Quoted text hidden]

Geeta Madhav Gali <gg6549@g.rit.edu> Mon, Feb 4, 2019 at 3:26 PM
To: Caitlin Melton <cmelton@compumedicsusa.com>
Cc: Curry8 Help <Curry8help@neuroscan.com>

Thank you very much Ms Melton.

> On Feb 4, 2019, at 3:17 PM, Caitlin Melton <cmelton@compumedicsusa.com> wrote:
>
> Hi Madhav,
>
> I am including our Curry team in the email chain and they will know of if there is an easier way to accomplish what you need. They are based in Hamburg, Germany and will reach out when they get back to their offices. Note they are in a different time zone, sorry for any inconvenience this causes.
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> Thank you,
> Caitlin Melton
> Clinical/Research Application Support Analyst
> Compumedics Neuroscan
> Main 877.717.3975
> Direct 704.749.3222
> Support 704.749.3202
> Fax 704.749.3299
>
> [Quoted text hidden]
> [Quoted text hidden]

Curry8 Help <Curry8help@neuroscan.com> Tue, Feb 5, 2019 at 4:14 AM
To: Geeta Madhav Gali <gg6549@rit.edu>
Cc: Curry8 Help <Curry8help@neuroscan.com>

Dear Madhav,

You can use a macro to cut your ongoing data into 1-second-blocks and create an image file with a topographic map.

Find attached a sample macro that creates 1 second long back-to-back epochs and then loops through those epochs and saves an image of the map from the first sample of each epoch.
Copy the .mac file to
C:\Users\<your_user_name>\AppData\Roaming\Neuroscan\Curry 8\Macros
to make it appear in Curry's macro list.

Open the .mac file in a text editor and see my comments. Adjust the loop
counter to match your number of desired maps images.
Go to Edit > Options > Hardcopies to adjust the dimensions of your maps
images.

Best regards
Reyko

On 04-Feb-19 21:17, Caitlin Melton wrote:
>
> Hi Madhav,
>
> I am including our Curry team in the email chain and they will know of
> if there is an easier way to accomplish what you need. They are based
> in Hamburg, Germany and will reach out when they get back to their
> offices. Note they are in a different time zone, sorry for any
> inconvenience this causes.
>
> Thank you,
>
> Caitlin Melton
>
> Clinical/Research Application Support Analyst
>
> Compumedics Neuroscan
>
> Main 877.717.3975
>
> Direct 704.749.3222
>
> Support 704.749.3202
>
> Fax 704.749.3299
>
> cid:image004.jpg@01D28EA5.EDEF32B0
>
> Confidentiality Note: This email transmission and any documents
> accompanying this email transmission contain information from
> COMPUMEDICS USA, Inc. which is confidential. The information is
> intended only for the use of the intended recipient. If you are not
> the intended recipient, you are hereby notified that any disclosure,
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> the documents should be returned to COMPUMEDICS USA,
> Inc. immediately. If you have received this email in error, please
> notify us immediately by email address set forth above.
>
> *From:* Geeta Madhav Gali <gg6549@rit.edu>
> *Sent:* Monday, February 4, 2019 3:03 PM
> *To:* Caitlin Melton <cmelton@compumedicsusa.com>
> *Cc:* Geeta Madhav Gali <gg6549@rit.edu>
> *Subject:* Re: Contact Submission from Madhav Gali via Compumedics
> Neuroscan Website
>
> May be I did not communicate properly.
>
> The project that I am currently working need Images(FD maps) to be fed
> into a machine learning model. Here are the steps that I am following
>
> 1. I collect the EEG data for a period of 14 minutes.
>
> 2. Once I did that, I need to generate 14 *60(1 image(FD map) for each
> second) images.
>
> The procedure that I knew until now is manually navigating to each
> second in the data that I collected and downloading the image(FD map).
> But is there a feature in the Curry 8 where I can click a button or do
> something so that I can get all the images(14* 60 which is 840 images)
> at once? This is my question.
>
> Please let me know.
>
> Thanks and regards
>
> Madhav Gali
>
>
>
> On Feb 4, 2019, at 2:40 PM, Caitlin Melton
> <cmelton@compumedicsusa.com <mailto:cmelton@compumedicsusa.com>>

[Quoted text hidden]

> *From:*Geeta Madhav Gali <gg6549@rit.edu <mailto:gg6549@rit.edu>>
> *Sent:*Monday, February 4, 2019 12:26 PM
> *To:*Caitlin Melton <cmelton@compumedicsusa.com
> <mailto:cmelton@compumedicsusa.com>>
> *Cc:*Tech Sup <techsup@neuroscan.com <mailto:techsup@neuroscan.com>>
> *Subject:*Re: Contact Submission from Madhav Gali via Compumedics
> Neuroscan Website
>
> Hi Ms Melton,
>
> Thank you for reaching out to me. I am using Curry 8. When I said
> FD map I am referring Function Data map. Please reach out to me if
> you need any more information.
>
> Have a great day.
>
> Thanks and regards
>
> Madhav Gali
>
>
>
>
> On Feb 4, 2019, at 10:36 AM, Caitlin Melton
> <cmelton@compumedicsusa.com

[Quoted text hidden]

> *From:*Compumedics Neuroscan Support
> <sales@compumedicsneuroscan.com
> <mailto:sales@compumedicsneuroscan.com>>
> *Sent:*Monday, February 4, 2019 9:00 AM
> *To:*gg6549@rit.edu <mailto:gg6549@rit.edu>
> *Cc:*Tech Sup <techsup@neuroscan.com
> <mailto:techsup@neuroscan.com>>
> *Subject:*Contact Submission from Madhav Gali via Compumedics
> Neuroscan Website
>
> From:
> Madhav Gali
> Rochester Institute of Technology

> Computer Science
> 1 Lomb Memorial Drive
> Rochester
> 14623
> United States
> gg6549@rit.edu <mailto:gg6549@rit.edu>
> 5854353011
>
> Message Body:
> Hi
>
> I am working on the collecting EEG data. I was able to see the
> FD map after. I am wondering if there is a way to generate FD
> maps for every milli second or every second and download the
> FD map images at once, instead of moving over to that time and
> downloading each FD map image individually.
>
> Thanks
>
> Use of information:
> Yes, I agree the data provided in this form may be shared with
> a local Compumedics Neuroscan representative in my region.
>
> ---
> This mail is sent via the Compumedics Neuroscan Website
> http://compumedicsneuroscan.com <http://compumedicsneuroscan.com/>
>

--
Reyko Tech

CURRY Helpdesk
Compumedics Neuroscan

*** Announcements ***

Clinical Neuroscan School
May 31 - June 2, 2019 in Summit, NJ, USA
For details, cponton@neuroscan.com

Neuroscan School
September 24-27, 2019 in Hamburg, Germany
For details, ingridmerten@compumedics.com

Neuroscan School
TBA, 2019 in Seoul, Korea
For details, benso@compumedics.com

Neuroscan School
TBA, 2019 in Hong Kong
For details, benso@compumedics.com

Neuroscan School
TBA, 2019 in Beijing, China
For details, rliao@neuroscan.com

Neuroscan School
TBA, 2019 in Taipei, Taiwan
For details, rliao@neuroscan.com

http://www.compumedicsneuroscan.com/events

CURRY 8: curry8help@neuroscan.com
CURRY 7: curry7help@neuroscan.com
CURRY 6: curry6help@neuroscan.com

http://compumedicsneuroscan.com/category/products/?tag=curry

Handelsregister / Trade register: HRB 716153 AG Freiburg i.B.
Geschäftsführer / Managing Director: David Burton
Steuernummer / TIN: 203/107/16988
USt-ID / VAT No.: DE815689046

1-sec-maps.mac
2K

Geeta Madhav Gali <gg6549@g.rit.edu> Tue, Feb 19, 2019 at 1:07 AM
Reply-To: gg6549@g.rit.edu
To: Curry8 Help <Curry8help@neuroscan.com>

Reyko tech,

Thank you so much. That macro helped a lot.

-Madhav Gali
[Quoted text hidden]
--
Best Regards,
Geeta Madhav Gali
585.435.3011
Computer Science '18

Geeta Madhav Gali <gg6549@g.rit.edu> Wed, Apr 3, 2019 at 11:16 PM
To: Curry8 Help <Curry8help@neuroscan.com>
Cc: Caitlin Melton <cmelton@compumedicsusa.com>

Reyko,

Thanks again for helping me. I have three more questions if you could answer that would be of great help. Please find them below.

1. In the previous emails you sent me a macro which creates Functional Data(FD) Map every second. Is it possible to provide me a macro which creates FD maps every milli second.

2. Is it possible to convert the acquisition file(.cdt file) to a text or a csv file with values of each sensor in it?

3. I am wondering if you could provide me some information on which sensors are collecting data from the which regions of brain such as prefrontal cortex etc.

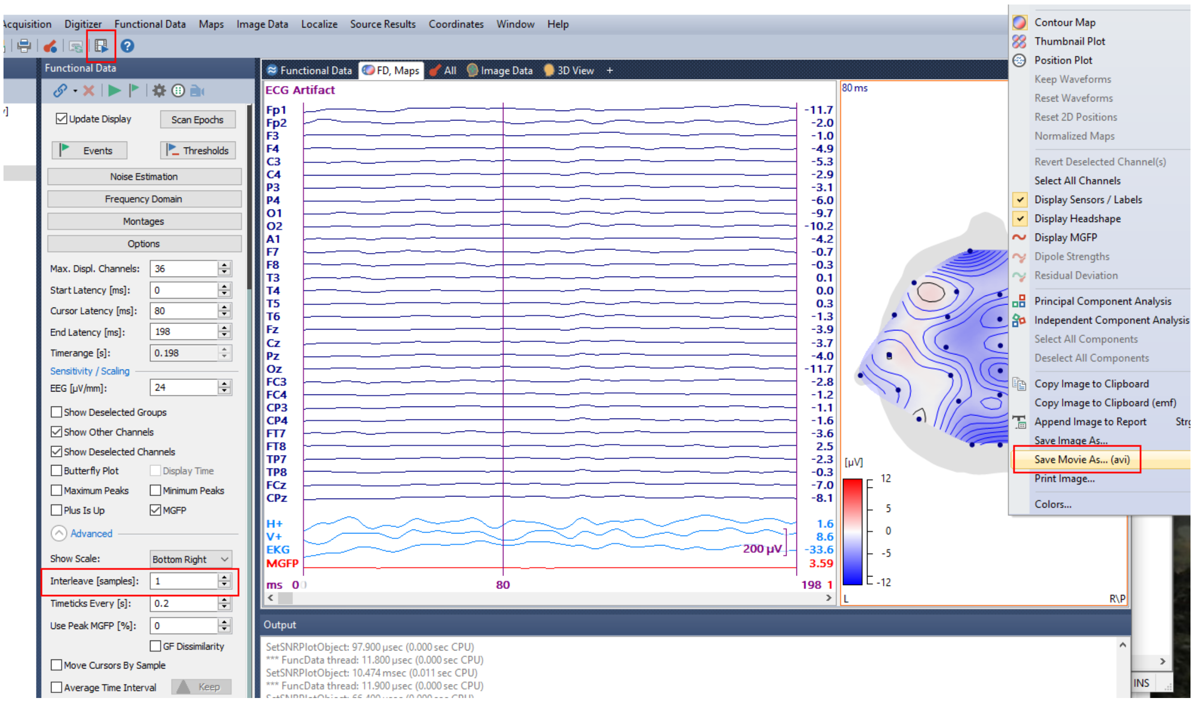
Thank you so much for your help.

Thanks and regards
Madhav Gali
[Quoted text hidden]

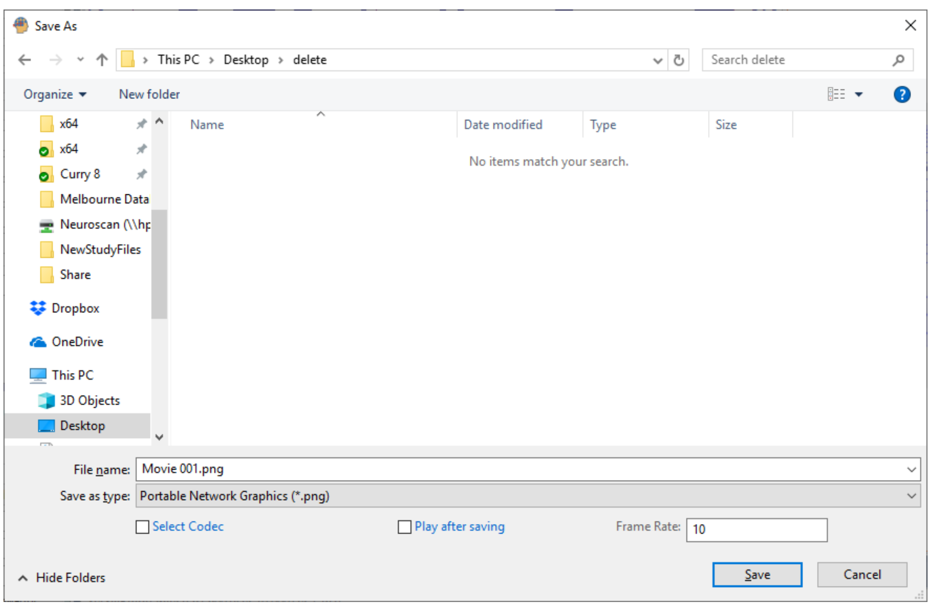
Curry8 Help <Curry8help@neuroscan.com> Thu, Apr 4,
To: Geeta Madhav Gali <gg6549@rit.edu>
Cc: Curry8 Help <Curry8help@neuroscan.com>, Caitlin Melton <cmelton@compumedicsusa.com>

Hello Madhav,

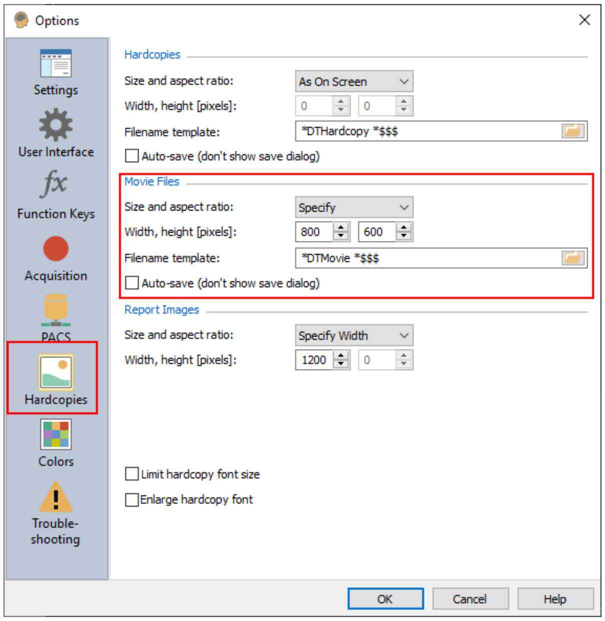
1.
You could modify the DataSplitIntoEpochs in the macro, but 0.2 sec is currently the smallest value for back-to-back epochs you can use.
Instead, if you need to create one map per millisecond, I would save a movie instead (mark the timerange you want to create a movie from, then right-click into the Maps display and select Save Mo
data file has a sampling rate higher than 1 kHz, you can use the Interleave option to skip samples.



If you set the movie file type to png, you will get single image files:



You can change/verify the resolution of these images in Edit > Options > Hardcopies:



In fact, you can use this Interleave and Save Movie option to create one map per second as well.

2.
Go to File > Functional Data > Save Data and select Curry Raw ASCII Format. The resulting .cdt file is a text file that contains one sample per row (one channel per column).

3.
If your recording has labels based on the standard 10-20 system, this information is embedded in the channel names:
https://en.wikipedia.org/wiki/10%E2%80%9320_system_(EEG)

Best regards
Reyko
[Quoted text hidden]

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